USE OF FUZZY LOGIC IN THE INTERPRETATION OF ELECTROCARDIOGRAMS

by

Frederick S. Albright

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SUPERVISORY COMMITTEE APPROVAL

of a thesis submitted by

Frederick S. Albright

This thesis has been read by each member of the following supervisory committee and by majority vote has been found to be satisfactory.

Chai[redacted]an Pryor, P[redacted].D.

Mark H. Skolnick, Ph.D.

Robert L. Lux, Ph.D.

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I have read the thesis of Frederick S. Albright in its final form and have found that (1) its format, citations, and bibliographic style are consistent and acceptable; (2) its illustrative materials including figures, tables, and charts are in place; and (3) the final manuscript is satisfactory to the Supervisory Committee and is ready for submission to the Graduate School.

Date

T. Allan Pryor
Member, Supervisory Committee

Approved for the Major Department

Homer R. Warner
Chairman, Dean

Approved for the Graduate Council

B. Gale Dick
Dean of The Graduate School

ABSTRACT

Interpretations of the electrocardiogram by expert systems are subject to error because of the presence of noise in the electrocardiogram, and extracted electrocardiographic features. The noise has several sources: physiological, electrical, and algorithmic.

The electrocardiographic diagnostic HELP frames use Classically formulated deterministic rules to interpret electrocardiographic data for myocardial infarction. The rules are written with absolute or "crisp" boundary conditions, and are evaluated according to binary logic. If the electrocardiographic wave data have significant amounts of noise, the rules are subject to errors in their interpretations (classification errors).

Using Fuzzy Logic and Set formalisms, Fuzzy rules can be created. Fuzzy rules use Fuzzy subsets to describe the electrocardiographic features, and a multivalent logic. Fuzzy membership functions ascribe the possibility or confidence that a datum is a member of a fuzzy subset, such as a significant q-wave or inferior infarction.

This particular project compares a Fuzzy rule to the Absolute Criterion from the HELP electrocardiographic analysis frames for relative classification error rates in the interpretation of inferior infarction.

The Fuzzy and Absolute Criteria were compared to each other in a study of serial interpretations from sequential electrocardiograms from computerized patient records of LDS Hospital. The Absolute Criterion was

more consistent in its intepretational patterns than was the Fuzzy Criterion when compared to the physicians' overread statements.

A Monte Carlo Simulation was developed to study the effects of noise on the intepretative behavior and stability of the Absolute and Fuzzy Criteria. If the Absolute (viz. the Relaxed Criterion) and Fuzzy Criteria have similar sensitivities and specificities, and data with the same amount of noise, then their intepretational behavior and stabilty profiles are not significantly different. If the gain is equal to zero, the Fuzzy Criterion mimicks exactly the Absolute Criterion in both intepretational behavior and stability. The gain of the Fuzzy Criterion alters the behavior profile of the Fuzzy Criterion. The Fuzzy Criterion appeared to be less prone to classification errors for inferior infarction.

In a second patient study, sensitivities, specificities, and positive predictive values were calculated for the criteria. Altering the gain of the Fuzzy Criterion altered the sensitivity and specificity of the Fuzzy Criterion. The Fuzzy Criterion was less prone to classification errors if the data were indicative of inferior infarction as shown by the higher sensitivity for the Fuzzy Criterion. However, the Fuzzy Criterion was prone to classification errors if the data were not indicative of inferior infarction as shown by a higher specificity for the Absolute Criterion.

This project has demonstrated the interesting possibility for the use of Fuzzy formalisms to augment the Bayesian and Classical formalisms employed in the HELP system for the interpretation of electrocardiograms.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Classical formalisms and Bayesian probabilistic theory are currently used in the HELP diagnostic system to represent medical concepts and make medical interpretations. This project was an attempt to explore and apply Fuzzy Set Theory (1) as a representation scheme for the imprecise medical concepts used to describe the symptomology and events of myocardial infarction in contrast to the Classical and Bayesian formalisms used in the HELP system. Fuzzy Logic and Fuzzy Set formalisms extend those concepts in Probabilistic Theory and Classical Logic and Classical Set Theory that deal with uncertainty and the representation of imprecise medical concepts and terminology. In addition, a Fuzzy Logic inferential mechanism was used to evaluate a Fuzzy rule developed in this project for the interpretation of inferior infarction. The Fuzzy rule used a Fuzzy Set representation of different data parameters as a basis for the interpretation. This project was also undertaken to explore the manner in which Fuzzy Logic deals with uncertainty and the process of medical decision making in contrast to the Classical deterministic rules of the cardiological analysis sectors of the HELP system. In summary this project explores the use and possible benefit of using Fuzzy Logic, to infer from primary electrocardiographic wave data the presence or absence of inferior infarction in light of the inherent uncertainty in the data and the decision making process.

1.2 Background

1.2.1 Human Experts and Expert Medical Systems

Information having a high level of imprecision poses problems for the human expert or practitioner. Imprecise information can be detrimental to their attentions and actions. A human expert is able to "see" through the noise or uncertainty and ascertain the essential informational elements in a noisy or imprecise decision making environment. This means that a practitioner can make accurate medical inferences and therapy treatments based upon "fuzzy" information, or "fuzzy" classifications of the symptomology of the patient into diagnostic sets that do not have precise or absolute boundaries (2,3). For example, the human expert understands that absolute test values, or the magnitudes of wave forms of the electrocardiogram, are actually imprecise or "fuzzy" concepts. The expert system interprets them as absolute concepts unless otherwise instructed. Fuzzy Set Theory and Fuzzy Logic provide a formal basis for the representation and interpretation of such absolutes as imprecise or "fuzzy" entities in an expert medical system. Fuzzy Logic and Fuzzy Set Theory (known from this point as Fuzzy Logic) provide an inherent logical and functional means of manipulating uncertainty in the data, knowledgebase and inference process (3). This is an alternative to "programming in" the rules or logic by the system developers to manipulate and classify the degree of imprecision in the data and inferences).

1.2.2 Fuzzy Logic in Medical Decision Making

Since the physician deals in such imprecise terms or "fuzzy" concepts and elastic or plastic decision processes, some researchers in medical decision making have felt that it is more appropriate to use a decision logic and knowledge representation that is not "crisp" or absolute in nature (4). Specifically, they have begun to explore, with some success, alternative logics and knowledge representations that are not binary. Instead of employing traditional or Classical Sets and Logic that are divalent, they champion the use of multivalent logics and elastic (fuzzy) set classifications. One example of these multivalent set logics is Fuzzy Set Theory and the associated logic and mathematics (5).

For example, Bortolan and associates (4) have employed a Fuzzy Logic knowledge representation scheme to interpret electrocardiographic information for myocardial infarction. They have stated that this approach offers two advantages over probabilistic and Classical deterministic rule based decision tree schemes because they combine the following features of both approaches: the physician is able to understand how the interpretation was made and find possible errors because the physician is informed about the reasoning path used and the physician is able to make a judgement as to what mutually exclusive diagnostic group the electrocardiographic information resembles and how reliable the automated interpretation is. In addition, with Classical deterministic rules small informational changes in electrocardiographic features near rule boundary conditions can cause significant interpretational or inference changes. However, Fuzzy deterministic rules based on Fuzzy boundaries tend to be less severely affected by such interpretational changes or instabilities.

Adlassnig and Kolarz (6) have described CADIAG-2, an expert medical system for diagnosis that is data driven, which uses Fuzzy sets to describe the symptomology of a patient and Fuzzy reasoning methods to diagnose internal medicine disorders. As part of this reasoning facility there are methods for the combination of evidence that ultimately provide a hypothetical diagnostic list (7). The representation of a patients symptomology uses linguistic terms from the patient record that are translated into Fuzzy sets in order to be evaluated by Fuzzy reasoning methods. So, in the knowledge representation scheme they have employed the concept of occurrence that describes the presence or Fuzzy membership of a symptom that occurs in a patient. They also utilized the concept of confirmability or power of a symptom to confirm a disease or diagnostic hypothesis. This too is a Fuzzy membership concept (8). Like other Fuzzy expert systems, this system also employs multivalent inference results and Fuzzy linguistic medical terms to both describe and interpret the symptomology of a patient. The system also provides details to the practitioner to explain its diagnostic results.

1.2.3 Uncertainty and Noise

Uncertainty and noise ultimately result from the imprecise knowledge or statement of truth about something, someone, or some event. In the context of this project, uncertainty has been considered to be synonymous with noise, although they do possess nuances of meaning that are different. Questions such as: "How confident am I that this person is experiencing chest pain caused by ischemia or heart disease?", or "How accurate is this measurement for a Q-wave magnitude?" illustrate the twin concepts of uncertainty (confidence that something is true) and noise (how close a laboratory value is to the population mean). Uncertainty in some sense describes one's belief in something, i.e., it is a descriptive or qualitative concept about truth and is conveyed via medical terms or linguistic concepts. Noise is a quantitative term that describes the precision of a measurable quantity and its population mean.

1.2.4 Sources of Uncertainty or Noise in Medical Decision Making

Noise in a medical decision making environment arises from several sources. It arises from the imprecision associated with medical tests and descriptions. Variability in the patient population is considered a source of noise. Electrical sources cause many problems in the precision of electrical devices which measure electro-biopotentials. In addition, the recording devices's electronics also are noise sources (9) . The techniques used to acquire or capture physiological biopotentials via analog and/or digital techniques, including wave form processing, can also introduce inaccuracies in the recordings of the original wave forms of the biopotentials.

Finally, there are the ubiquitous language and knowledge-related sources of uncertainty. How precisely does medical terminology describe clinical phenomena? Is the terminology not fraught with imprecision? It is often descriptive (qualitative), instead of quantitative in nature. Unlike a lab test value, which can be expressed as how close it is to a population mean (in the sense of standard deviations from the mean), it is difficult to express a descriptive term for a clinical finding in such terms. For example, a significant Q-wave finding in an electrocardiogram is indicative of infarction. The term significant carries no measurable quantity of error. Although it is an imprecise term (linguistic concept), its meaning is exact and crucially important in the diagnosis of inferior infarction based upon electrocardiographic features. It is a "fuzzy" concept. So, the use of the term "significant Q-wave" in making an inference for infarction becomes an exercise in how confident the practitioner is that a Q-wave is representative of a significant Q-wave and that this significance in turn is suggestive of infarction.

In the end, the issues of uncertainty in a medical decision making environment are summarized when practitioners continually ask, "What do we not understand about medicine, what have we not discovered?" or "What are the important facts about the patient, what remains to be done to improve the health and well being of the patient?" Medicine is a science full of endeavor and success, but it is not a completed discipline. It remains a science of discovery and experiment.

1.2.5 Uncertainty and its Implications for Patient Care and Outcome

In medical decision making environments (viz. the human practitioners and expert systems involved with patient care) it is particularly important that methodologies are developed that effectively counteract the detrimental effects of informational entropy in medical decision making (the tendency for disorder in medical information and decision making). For instance, diagnostic tests often reduce the level of uncertainty. Even so, the imprecision cannot be reduced completely. Many lab tests have an associated high level of uncertainty or indefiniteness (10). In other words, the data can retain a degree of uncertainty that a practitioner or particular medical expert system cannot deal with effectively in order to make a correct inference or properly provide for the care of a patient. This is especially true if the "expert" unknowingly makes an important medical decision based upon such "bad" information. An incorrect assessment or interpretation about a patient's condition resulting from imprecise information could lead to unnecessary therapy or the omission of needed therapy, either through the inference from data that are "bad" because they are so noisy as to be meaningless, or the employment of an interpretation methodology or cognitive model in an inappropriate context. In addition, an incorrect decision could increase the noise or uncertainty in the medical history or status of a person requiring medical attention, which could result not only in incorrect decisions in the future, but future medical information complications as well.

The criteria for inferior infarction in this project utilized electrocardiographic wave magnitudes in order to "make an interpretation." These electrocardiographic features and others are important to diagnosing cardiomyopathies. The next section serves as a brief summarization of the myocardium, function of the heart, its tissues, electrochemical events, heart vector, where the heart vector originates, lead systems and the electrocardiogram. The section concludes with the pathophysiology of myocardial infarction, its effects on and uncertainty in the electrocardiogram.

1.2.6 The Myocardium

The heart or the myocardium is the muscular "pump" of the body that delivers oxygenated blood to the body and deoxygenated blood to the lungs to replenish the oxygen lost to the tissues of the body during cellular metabolism.

The myocardium is composed of several types of specialized tissue. Some cells (cardiac muscle cells) are responsible for the contractions of the myocardium. Other cells (conductile tissue; specialized cardiac muscle tissue) provide more efficient pathways than the contractile muscular tissue to carry the cardiac electrochemical impulse (action potential) to different regions of the heart. Finally, there are other tissues in the heart that provide structural support (e.g., connective tissue and tendons) and aid the pumping activity of the heart. For instance, the cardiac atrial-ventricular valves restrain the flow of blood back into the atria when the ventricles pump. The backflow of blood from the pulmonary artery and aorta when the ventricles fill with venous blood is restrained by the pulmonic and aortic valves.

1.2.6.1 Action Potential, Depolarization and Repolarization

In order for the heart to contract rhythmically, it has a "natural" pace maker, the sino-atrial node. Like the rest of the myocardium, this tissue has the property that it will depolarize/repolarize on its on accord. But, unlike the other myocardial tissue, its refractive, or resting phase, is shorter. Hence, it "paces" the myocardial depolarization/repolarization events in the myocardium (9, 11, 12).

The sino-atrial node begins the depolarization of the myocardium and gives rise to the action potential that causes the cardiac muscle tissue to contract. The action potential is propagated throughout the myocardium in a coordinated manner by specialized conductive tissue and cardiac muscle cells (12). Myocardial contractions force the blood to flow from the chambers of the heart into the arteries, thence to the tissues of the body. The depolarization wave is followed immediately by the polarization wave, which returns the myocardium to its resting electrochemical state, the resting potential. Soon after the polarization wave passes through myocardial tissue, the heart muscle relaxes and its chambers fill with blood from the veins leading to the heart. The contraction/relaxation events begin normally upon the initiation of the depolarization wave by the pace maker after the refractory, or resting phase is over (12).

1.2.6.2 Ionic Events of the Cardiac Cycle

The action potential is the result of sequential depolarizations of the myocardial cells. Depolarization occurs when the cell membrane of the myocardial cells permit a rapid or catastrophic influx of sodium ions, via rapid diffusion of the sodium ions through the cell membrane into the cytoplasm of the cell (11). During the depolarization phase, potassium ions diffuse rapidly out of the cell. In the normal heart, the depolarization events of a membranous region make neighboring membranous regions "leaky" or freely permeable to sodium. The depolarization sequence is self-propagating (11).

Polarization (viz. repolarization) soon follows depolarization. Polarization begins with an increase in the flow of potassium ions into the interior of the cells and a net flow of sodium ions out of the cell. The cellular "machines" responsible for the repolarization of the membrane are ion pumps in the plasma membranes, namely electrogenic pumps. These sodium-potassium pumps preferentially transport sodium out of the cell and potassium into the cell in order to establish an ionic gradient across the plasma membrane (12). The gradient makes a potential difference between the inside and outside of the membranes. Polarization ends when the myocardial tissue reaches its resting potential (12). The myocardium has now been prepared for the next depolarization.

1.2.6.3 The Cardiac Dipole

The depolarization, polarization and refractive events of the myocardial cells give rise to millions of dipoles when the myocardium is viewed on the scale of the millions of ionic regions of cell membranes. The dipoles result from the changing charge distributions or ionic movements and "static" charges or ions over the entire myocardial cellular membranes (11).

The ionic current flows (moving ions) give rise to charge flows or electrochemical currents in the myocardium. An individual charge and/or its movement (charge flow) can be viewed as a charge dipole (or simply dipole), which has a vector representation in three dimensional space. A vector representation allows an individual charge (dipole), or the average net charge of a group of ions, or dipoles, to be represented with a direction attribute and magnitude of charge attribute.

Dipoles in an electrolytic solution or medium (i.e., a solution that can conduct electricity, e.g., a salt solution, or the body) produce lines of current flow throughout the medium (11). A current field is produced. Myocardial depolarizations and repolarizations produce changing dipoles or biopotentials in the body since ions are moving across celluar membranes. Collectively, the dipoles give rise to the cardiac dipole or heart vector, the instantaneous collective biopotential of the heart (11).

1.2.6.4 Cardiac Electrochemical Events Are Recorded with the Electrocardiogram

Researchers and clinicians alike can view the changing biopotential of the heart over time, by measuring it with a set of electrocardiographic leads placed on the body and connected to an electrocardiographic device, which amplifies the changing biopotentials of the heart and filters out most other extraneous electrical activity or noise (9, 11). An electrocardiogram is produced that is a record of the changing cardiac dipole or heart vector over time. The vectorcardiogram is a planar representation of the cardiac dipole. It shows the magnitude and direction of the cardiac dipole, in the different three-dimensional image planes: frontal, horizontal and sagittal. The electrocardiogram and vectorcardiogram provide important information about the electrochemical action of the heart and are very good indicators of the contractile (pumping) activity of the beating heart (11).

1.2.6.5 Orthogonal Lead Systems

This type of lead system is based upon the fact that all the dipoles that result from depolarization, repolarization, and refractive events of the heart can be collectively interpreted as one vector, the cardiac dipole or heart vector. To accurately measure this heart vector, orthogonal lead systems have been proposed.

Such electrode systems make several assumptions. First, the heart vector originates in the center of the heart and the leads can be placed to accurately record the heart vector. The leads are grouped into different electrodes. The resulting electrode configuration forms planes through the body (image planes) which are oriented and aligned with those of the heart vector. These image planes intersect perpendicularly at the origin of the heart vector. Hence the adjective, orthogonal, is used (11).

The three planes are the frontal (formed by the XY-axes; corresponds to a frontal cross sectional view of the body through the center of the heart), horizontal (formed by the XZ-axes; corresponds to a horizontal cross sectional view through the center of the heart), and the sagittal (formed by the YZ-axes; corresponds to a side view of the body in cross-section through the center of the heart) planes (11).

However, the heart dipole is off center from the heart. The heart is rather amorphous in shape and inconsistent in physical/electrochemical make-up. The conducting medium of the heart and body is neither homogeneous, regularly shaped, isotropic, or finite in size (11). Lungs, bones, tissue fluid and blood vessels make the conduction medium inhomogeneous. The electrical properties of the body and heart are not uniform. Variations in how the heart vector is measured occur, leading to different recordings of the electrocardiogram or vectorcardiogram. Since it is so very difficult to align lead axes precisely with the heart vector axes and its origin, along with the other factors as mentioned above, the "measured" or recorded heart vector from a lead is unequal in strength to the "real" heart vector. Consequently, the vectorcardiograhic or electrocardiographic recording of the cardiac dipole's magnitude does not truly equal the magnitude of the cardiac dipole (11).

1.2.6.6 The Frank Lead System: A Corrected Orthogonal Lead System

To circumvent these difficulties, corrected orthogonal lead systems, like the Frank system, have been developed (11). It was experimentally developed and based on placement of leads upon models of the human torso filled with electrolytic solutions and human subjects. Resistor networks were developed in the experimental models to reduce the effects of the variability of lead placement and individual conductive medium differences. The Frank System also assumes image planes (leads) are orthogonal and can be aligned with the heart vector (11).

The Frank system uses seven leads. Since it is a corrected orthogonal lead system, the leads or electrodes are connected through a weighted resistor network. This is a practical approach to equalize the electrodes or nullify the inconsistencies in the conduction/measurment of the cardiac or heart dipole. Leads a, c, and i make up the X electrode (to record the horizontal projection of the heart vector); leads f, m, and h make up the Y electrode (to record the vertical or frontal projection of the heart vector) and leads a, m, i, e, and c make up the Z electrode (to record the sagittal projection of the heart vector) (11).

In this project, all measurements of the electrocardiogram and electrocardiographic features were measured by the Y electrode (the vertical frontal plane) of the Frank lead system.

1.2.6.7 Normal and Abnormal Features in the Electrocardiogram

Figure 1 displays some common features of the electrocardiogram. The reader will notice that magnitudes and a periodicity are associated with each wave form. What do these features tell about the activity of the heart

The P-wave is the beginning of the heart cycle. The P-wave begins with

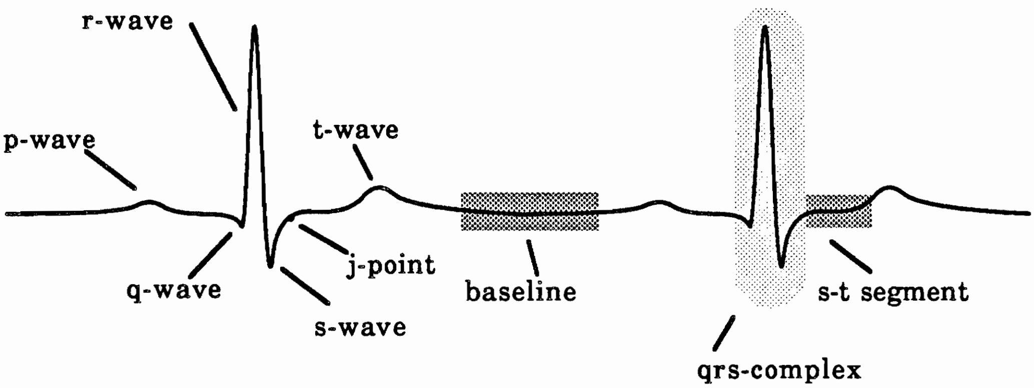

FIG. 1. Common Electrocardiographic Features of electrocardiograms.

the depolarization of the sino-atrial node. The P-wave includes the action potential caused by the sino-atrial node (pacemaker) depolarization and the depolarization events of the atria. Atrial contractions follow soon after the P-wave. The atria deliver about 30% more blood to the ventricles than would actually be delivered without their support (12). The atria act as "supercharger" pumps for the ventricles, especially during physical exertion or increased demand for cardiac function. The repolarization wave of the atria is masked by the QRS complex.

After the P-wave, there is a flat region in the electrocardiogram, the P-R segment. The P-R segment plus the P-wave comprise the P-R interval. During this interval, the action potential has been delayed by the specialized conductive tissue of the A-V node, the atrial-ventricular node (12). This delay gives the atria time to complete their pumping stroke to fill the ventricles before the initiation of the ventricular pumping stroke. Normally the P-R segment is coincident with the baseline, which is the isoelectric line. However, the P-R segment is slightly negative. So, in many electrocardiograms its tracing is underneath the baseline (11).

The next feature of the electrocardiogram is the QRS wave or complex. This feature's tracing is a record of the action potential movement throughout the ventricles. However, the left ventricle is the main ventricular component of the QRS complex because of its greater muscle mass and strength of contraction (12). In normal electrocardiograms, the Q-wave, which is the initial negative deflection, is of small magnitude or is not present. It is insignificant. However in ischemic, infarctive, or necrotic conditions of the heart the Q-wave can become more prevalent, or significant. Therefore significant Q-waves or changes are diagnostic cues for infarction originating in the ventricles, or other disease conditions of the heart (11). The first positive deflection after the P-R segment in the electrocardiogram is called the R-wave. The S-wave is the negative wave following an R-wave.

The interval following the S-wave is the S-T segment. During this time the ventricles have depolarized completely and consequently begin to pump and empty the blood into the arteries leading from the heart. The J-point ends the QRS complex and begins the S-T segment. In acute ventricular cardiomyopathies, the S-T segment can be elevated, depressed, downward sloping or upward sloping (11).

The T-wave occurs during the repolarization of the ventricles and its height or amplitude is proportional to the QRS complex, the depolarization event of the ventricles. Ischemic conditions can cause the T-wave to become inverted. If there are significant Q-waves present in conjunction with deep symmetrical T-waves, then a recent infarction is indicated (11). Massive injury or necrosis and connective tissue replacement of a ventricle (as in an old injury) can also cause repolarization to be prolonged (12). The T-wave can be altered not only in the shape of its waveform in cardiomyopathies, but its magnitude can be reduced as well.

After recovery, the T-wave tends to return to an upright pattern. Hence, old infarctions can be identified by an altered QRS complex (e.g., significant Q-wave) and a normal appearing (i.e., upright) T-wave.

The Q-T interval is that part of the electrocardiographic tracing between the QRS complex and the end of the T-wave. During this time the ventricles complete their pumping cycle and at the end of the interval relax and venous blood flows into them during the T-P segment, thus prepping the heart for the next pumping cycle, which is initiated by the upcoming P-wave (12).

1.2.6.8 Coronary Heart Disease and Ischemia

Ischemia, or lack of a sufficient blood supply to any region of the heart, can result in ischemic zones. This is the pathophysiological result of coronary heart disease. If the blood supply is so poor to an area that cardiac muscle function cannot be sustained, the affected region of the heart is said to be infarcted (12). What causes this deficiency in the coronary blood supply to an ischemic zone?

Coronary arteries, the arteries which deliver oxygenated blood to the heart, can become occluded or blocked via blood clots or coronary plaques. Coronary plaques are caused by cholesterol deposits or associated fibrous masses, or calcium carbonate deposits along the epithelial lining of a coronary artery (12). The condition of plaques existing in the coronary arteries is called atherosclerosis. In addition, injury or irritation of the lining of the coronary artery (perhaps related to atherosclerosis) can cause a local spasm that can lead to an acute coronary occlusion (12). Such events can also lead to the formation of a coronary clot or thrombosis. This type of event can occur quickly, with dangerous and life-threatening consequences.

1.2.6.9 Myocardial Infarction

Eventually, if the deficiency in the blood supply is not corrected by removal or reduction of these occlusions, extensive localized tissue damage and death of the myocardium can occur through the following process, which is called myocardial infarction.

If a coronary artery is blocked, oxygenated blood cannot be delivered to regions after the occlusion. However, collateral blood can enter the affected regions. Yet, the direct blood flow away from the effected regions has stopped because of the low blood pressure caused by the occlusion. The blood stagnates. Edema results, compounding the circulation problems. Eventually, complete oxygen depravation in the affected tissue results (12). Tissue death quickly follows any severe oxygen deprevation. The tissue becomes necrotic and cannot be repaired. Connective tissue eventually replaces the necrotic myocardium (12). In regions of the heart that have experienced repair via connective tissue replacement of unhealthy myocardial tissue, different electrochemical properties from that of healthy tissue are exhibited.

1.2.6.10 Damaged Myocardium Alters the Electrocardiographic Features

The damaged necrotic area of the heart (say a ventricular area, such as associated with an inferior infarction) alters the heart vector since the collective effects of its source, the millions of dipoles, are no longer the same. The damaged area is no longer the same in its expression of the electrochemical events of the heart cycle. These areas remain depolarized at all times (negatively charged surfaces) giving rise to the "current of injury" (12). In many cases this results in a lower baseline recording of the electrocardiogram. In addition, the action potential or depolarization wave in the heart as it approaches the infarcted zone now no longer has as many dipoles in the positive direction or pointing towards the electrode. If a number of them occur or the damaged area is substantial, then this results in a strong or significant initial negative deflection in the electrocardiogram, the Q-wave of the QRS complex. This is why a significant Q-wave is such an important indicator of infarction related to the ventricles, usually the left. Since the QRS complex and the T-waves are positively correlated, the polarization of the ventricles thus produces changes in the T-wave, e.g., a deep or negative T-wave. The associated changes in the S-T segment can be attributed to a like phenomenon and the current of injury (12).

1.2.6.11 The Electrocardiogram and Myocardial Infarction

From the above explanation of normal and abnormal features of the elecrocardiogram, it should be apparent that the electrocardiogram is a valuable clinical tool for the diagnosis of abnormal activities and conditions of the heart. It is painless, economical, noninvasive, reproducible, standardized, and easily performed. The electrocardiogram is used extensively in the diagnosis of arrhythmias, myocardial infarction, myocardial hypertrophy, pericarditis and systemic diseases that affect the heart and show particular rhythmic, pattern, or magnitude changes of the biopotentials of the myocardium (11).

1.2.6.12 Other Clinical Indicators of Myocardial Infarction

In addition to the electrocardiogram, a diagnosis of cardiac malfunction or an abnormal myocardium must also be based upon clinical findings: health of the patient, history, associated lab tests, and a physical exam of the patient.

1.2.6.13 Uncertainty in the Electrocardiogram

As the preceding paragraph has hinted, the electrocardiogram is not a perfect information source of the heart. For example, it is well-known that a normal electrocardiogram does not necessarily preclude a problem with the myocardium. Normal electrocardiograms have often been recorded in people with heart disease. The pathological process must first disturb the electrical activity and integrity of the heart before it can even begin to be measured by electrocardiography (11). In addition, abnormal electrocardiograms have been obtained from individuals with hearts that are normal (11). Finally, pulmonary diseases can also affect the electrocardiogram dramatically and thus can either be confused with cardiac disease or even mask the presence of a heart condition (11).

The electrical and computer components of the electrocardiographic measuring device are not capable of removing all sources of noise or extraneous elements in the electrocardiographic recording. Noise sources include: the electrical fields external to the electrocardiographic device, electrical fields internal and properties of the electrocardiographic device, electrode placement, poor contact of the lead and skin, physiological noise, patient variability, and unexplained sources of noise (9). Noise adds components of imprecision to the wave forms measured by the electrocardiogram and hence to the interpretation or diagnosis of cardiac malfunction of the heart.

1.2.6.14 Imprecise Terms and the Interpretation of Electrocardiograms

Imprecise linguistic terms ("fuzzy") terms are often used to describe or characterize electrocardiographic features. For example, qualitative terms such as significant or distinct Q-wave, abnormal T-wave, small P-wave, broad QRS, and others are used. These types of descriptors are used by the cardiologist or electrocardiographer to describe the electrocardiogram and are treated as symptoms that are used to confirm or deny a diagnosis (13). Hence the physician often uses imprecise terms to describe either the patient information, as symptoms, or the uncertainty of the information used in the diagnostic process. Also, the diagnostic process or decision process is often elastic or plastic in nature. "Fuzzy," floating, or imprecise decision boundaries, different decision criteria, or other processes are used to reach a clinically significant interpretation from the patient information or symptoms.

1.2.7 The HELP System and the Evaluation of Inferior Infarction

In the HELP system, there are many sectors that together as a block comprise the electrocardiographic analysis program. These sectors review, analyse, and evaluate the patient data for different types of cardiac dysfunction. This project has focused on two sectors that evaluate patient electrocardiographic data for inferior infarction or nondiagnostic Q-waves. The patient data had been originally recorded by an electrocardiographic system using the Frank lead protocol. The electrocardiographic system was able to analyze the basic electrocardiograms and through an interface with the HELP system patient data base, record the wave magnitudes from the different leads into the patient's medical record.

The HELP system has two Classical deterministic rules that evaluate the data in the patient record for inferior infarction using data provided by the Y-lead of the Frank lead system. These two rules, the Absolute Criterion and the Relaxed Criterion, are shown in Figure 2. The Relaxed Criterion is a more "complex" descendant or counterpart to the Absolute Criterion. The Relaxed Criterion has two additional connectives and another clause, which is made up of two subclauses.

Whereas the final evaluation of the Absolute Criterion is either a negative or positive interpretation for inferior infarction, the Relaxed Criterion uses a final evaluation of either positive or negative for nondiagnostic Q-waves. In some sense, the Absolute Criterion was "relaxed" in order to make the Relaxed Criterion. This is explained in the

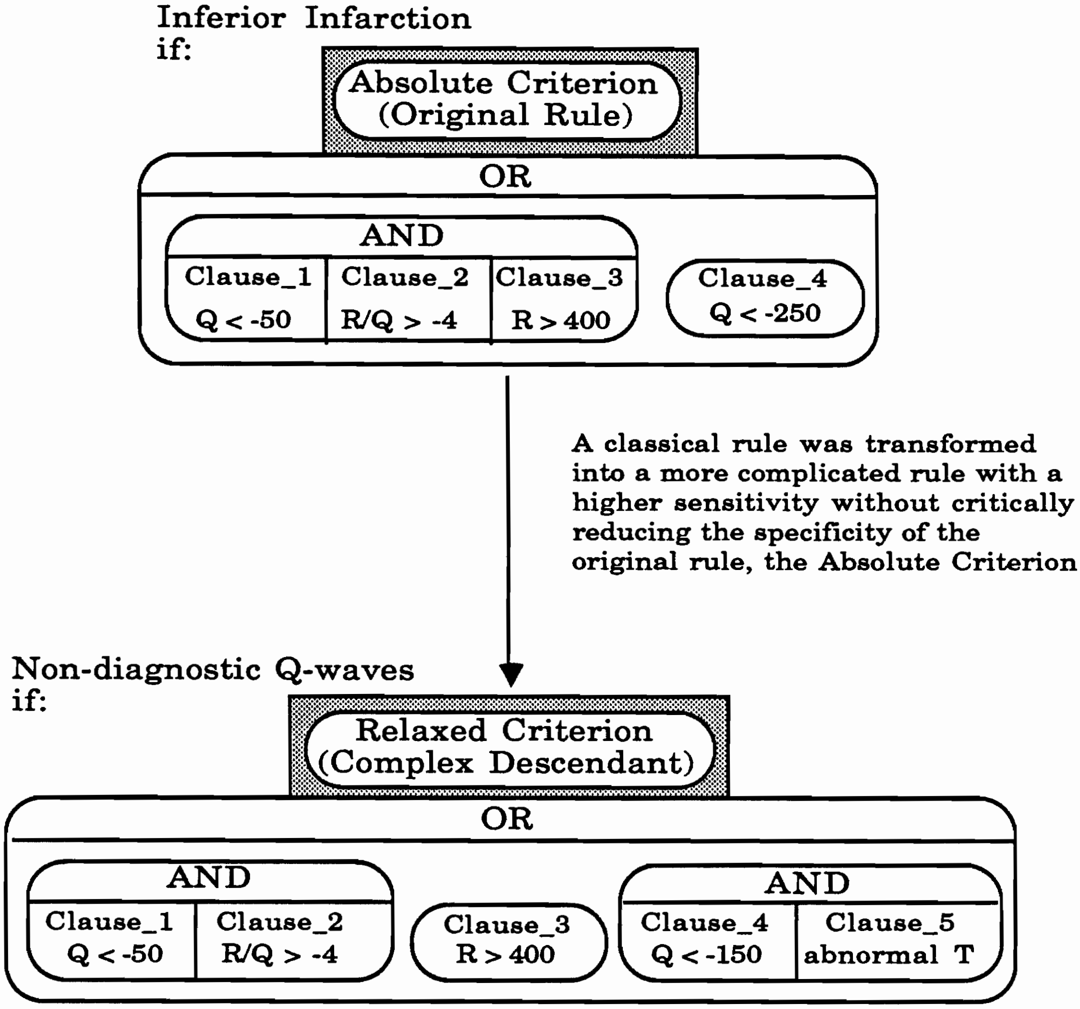

FIG. 2. The Absolute Criterion is Transformed into the Relaxed Criterion. A Classical rule was transformed into a more complicated Classical rule, which has increased sensitivity without a critical reduction in the associated specificitity.

The relationship between the clauses of the rules are shown, along with the differences between the logic of the two. The Q-wave magnitude in clause_4 of the Absolute Criterion was relaxed to -150 microvolts in the Relaxed Criterion, clause_3. Clause_3 of the Absolute Criterion was deleted in the Relaxed Criterion. Clause_4 and clause_5 were added to the Relaxed Criterion and connected by an "AND". The clause groups were then connected by an "OR". The interpretation of the Absolute Criterion is for inferior infarction whereas that of the Relaxed Criterion is for the presence of nondiagnostic Q-waves, which is indicative of inferior infarction if recorded in the Y-lead. In this project these two interpretations were considered to be equivalent.

paragraphs that follow.

From the studies of Pryor (14), the Absolute Criterion was shown to be very strict in its interpretation for inferior infarction. In other words, this rule exhibits a high specificity, but the sensitivity is low. If only this rule were used, too few true positives would be recognized and or too many false positives would occur in the clinical evaluation process. However, relaxing the boundaries, deleting a clause, and adding another clause with the correct logical flow, could produce a rule with a higher sensitivity without a concomitant critical loss of specificity. Hence Pryor (14) increased the second Q-wave boundary in the Absolute Criterion from -250 to -150 microvolts and introduced a third clause consisting of two subclauses connected by an "and." The effect of this clause is to compare the magnitude of the Q-wave with the T-wave character. Finally, the magnitude of the R-wave is removed as a limiting parameter in the rule. This transformation process produces the Relaxed Criterion.

For the purposes of this project, nondiagnostic Q-waves in the Y-lead are equivalent to an interpretation of inferior infarction. An abnormal T-wave in this case meant either an inverted T-wave or a nonexistent T-wave. These criteria are listed in Appendix A.

1.3 Project Description and Goals

This project was carried out to determine if a Fuzzy Logic and Fuzzy Set Theory approach to implementing decision logic for myocardial infarction (using inferior infarction rules as a test case) was a viable alternative to the current inferior infarction deterministic rules of the HELP diagnostic system in dealing with uncertainty. The determination of whether or not this Fuzzy Logic approach was a viable alternative to the classical formalism of the HELP system was based upon the relative interpretational results of the different criteria for infarction under the following concepts. These concepts could be considered important attributes of an expert electrocardiographic interpretational system in dealing effectively with uncertainty (16).

1.3.1 Important Attributes of an Expert Electrocardiographic Interpretational System

First, an expert system should exhibit consistent behavior when given serial electrocardiographic information. The question this concept posed was: which rule exhibits a greater interpretational consistency between patient derived serial electrocardiograms? This is an important "physician-like" behavior for an expert system.

Second, an expert system should not experience undue instability in its interpretational statements under varying conditions of noise. The evaluations should be correct and consistent for electrocardiograms with low to high levels of noise. Like the human cardiologist, the medical expert system should be able to make correct inferences in the presence of noise. The question posed was: which rule exhibits a greater degree of interpretational stability with respect to noisy electrocardiographic information? Another way of posing this question is: are the electrocardiographic interpretations of a particular rule stable if the underlying data elements have had noise randomly added to them? A simulation could give valuable information to attempt an answer for this question.

Third, it is desirable for the expert system to mimic as closely as possible the diagnostic statement behavior of the physician and always be correct. One would like the expert system to interpret truthfully; i.e., "tell the truth." This concept posed the question, which rule mimicked the interpretational behavior of the physician more effectively?

Finally, it would be a desirable feature of a diagnostic rule that it be easily modified or adapted to be applicable in a variety of clinical conditions. It should be possible to change its behavior from very conservative in its inference to very aggressive in its interpretational behavior for inferior infarction. In other words, can the interpretational behavior of a Fuzzy rule for inferior infarction be easily altered and what does this mean in terms of its subsequent interpretational behavior in relation to the Classical rules of the HELP system and the physician? Although it would be difficult, if not impossible, to answer this question in the affirmative at this time, a means to alter the interpretational behavior was developed for the Fuzzy rule that illustrates how simple it is to change the interpretational behavior of the Fuzzy rule.

The answers for the original question and the member questions of its decomposition are based upon how the interpretations of the rules compare with that of the physician's decisions (which were considered to be error free), how stable inferences from the rules with serial electrocardiograms (once again the physician's serial interpretations were considered error free) are, and how the rules' interpretational behaviors, and inferential stabilities (a consistency measure) compare in a Monte Carlo simulation in which the level of noise has been modeled.

1.3.2 Context Was not Considered as an Issue in this Project

The project described in this paper focused on developing a methodology to effectively deal with the imprecision or noise inherent in electrocardiograms and the uncertainty involved with an automated medical decision . It also focused on the development of Fuzzy Logic and Fuzzy Set Theory formalisms that could represent imprecise medical terms, such as significant Q-waves, as discrete membership functions. Q-wave magnitude values could then be compared to the functional representation of significant Q-waves and a confidence value or membership value in the set of significant Q-waves could be assigned. Using these values as logical parameters, the Fuzzy rule could then make an inference from the membership of the data in the diagnostic set , inferior infarction.

However, even though the author has mentioned the context in which rules can be applied, this project does not directly address the problems encountered concerning the contextual application of rules for electrocardiographic interpretations, knowledge representation schemes, or associated inference mechanisms. In this project, it was assumed that the contexts in which the rules for inferior infarction were applied were correct, with zero certainty that the rules could not be applied.

1.3.3 Brief Description of Fuzzy Formalisms as Used in this Project

This section gives a brief introduction to Fuzzy Set Theory and Fuzzy Logic (16, 17) through the explanation of how the Classical rule, the Absolute Criterion, was transformed into a Fuzzy rule, the Fuzzy Criterion and how the Fuzzy rule was used to evaluate the electrocardiographic data for inferior infarction. Figure 3 encapsulates the transformation in a concise representation.

1.3.3.1 Introduction of Fuzzy Logic through a Fuzzy Transformation

The Absolute Criterion was transformed into a Fuzzy rule, the Fuzzy Criterion, through the use of a Fuzzy "transformation." Each clause of the Absolute rule can be perceived as a Fuzzy subset. The appropriate electrocardiographic datum will have a degree of membership in the clause. Each clause of the Absolute Criterion was "fuzzified," or transformed into a fuzzy-subset. Through a sequential application of Fuzzy Set Theory formalisms to each clause of the Absolute Criterion, the "fuzzy" medical linguistic term, significant Q-wave in the Y-lead, can be represented as a Fuzzy membership function or as in this case, a Fuzzy subset. Hence a Q-wave from a particular electrocardiogram will have a degree of membership in the set of significant Q-waves.

1.3.3.2 Fuzzy Membership Functions and Confidence

An inherent feature of Fuzzy Logic is the use of Fuzzy membership functions or Fuzzy subsets to ascribe membership of a particular datum or

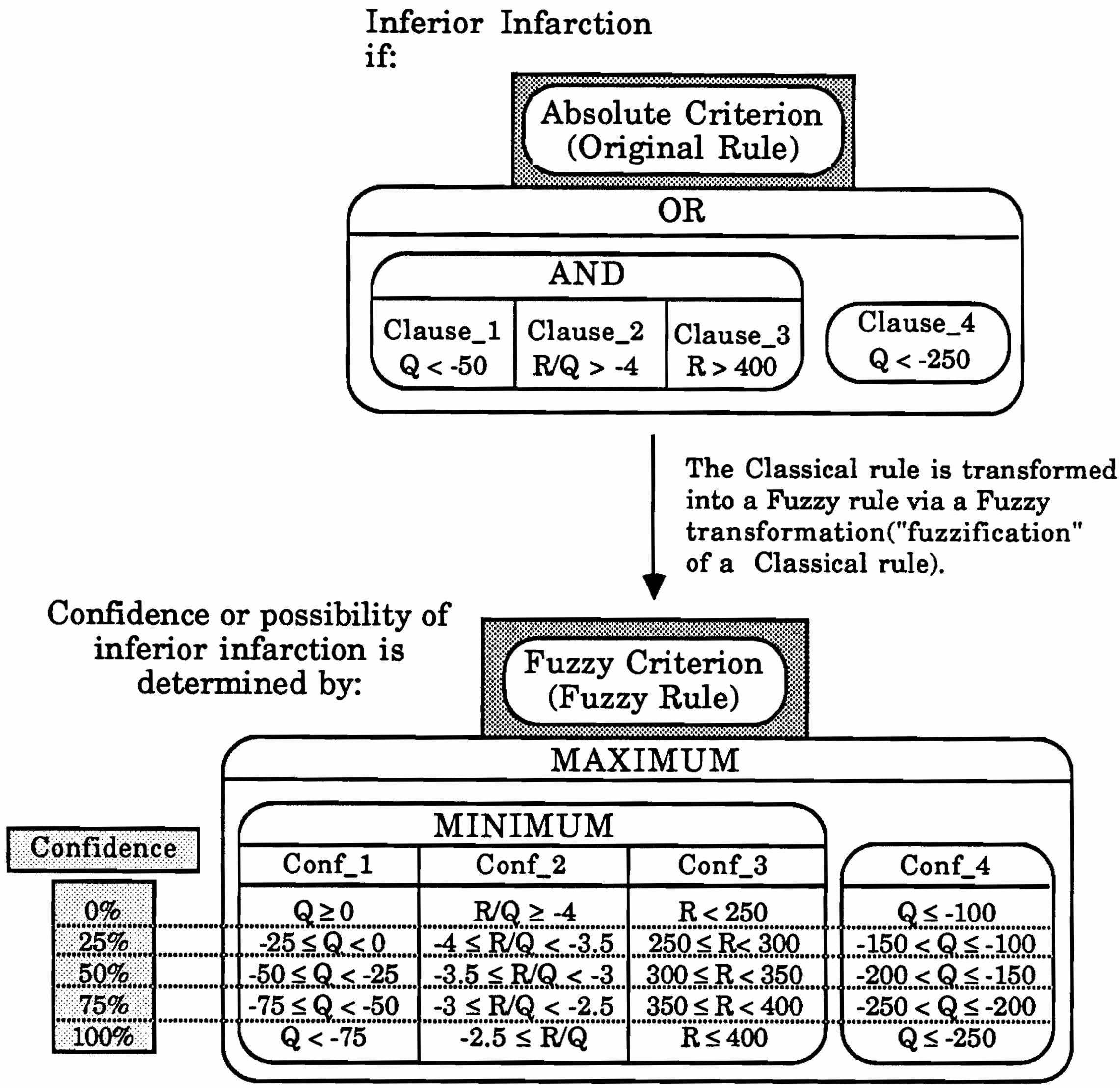

FIG. 3. Transformation of the Absolute Criterion into the Fuzzy Criterion. The Classical rule, the Absolute Criterion, is transformed into a Fuzzy rule, the Fuzzy Criterion. The connectives become MAXIMUM (for the "OR") or MINIMUM (for the "AND") operations for the determination of the confidences of each Fuzzy clause, represented by Conf_1, Conf_2, Conf_3, and Conf_4. Each clause of the Absolute Criterion was transformed into a Fuzzy subset that is discretely described by the confidences: 0%, 25%, 50%, 75%, and 100%. These confidences correspond to the linguistic terms: definite, probable, possible, consider, and not possible. These terms are used to describe the certainty or possibility that the information represents inferior infarction.

linguistic term such as a significant Q-wave, to a particular propositional clause of the Fuzzy rule. The Fuzzy subset or its membership function for each clause was used to ascribe a membership value of a particular data item. Membership values are elements of [0, 1], i.e., can have any real value between 0 and 1, inclusively. Values within the interval, or middle values, are allowed to describe the membership of a datum in a set or the certainty of an evaluation or possibility inference of a rule. Middle values can also be used to describe the confidence or certainty for the application of a rule to a particular situation. This contrasts with a Classical set or the truth evaluation of a Classical rule in which only 0 or 1 values are allowed for the truth value of a datum. No middle value between 0 and 1 is allowed, i.e. an element is either a member of a set, or it is not a member; a rule is either true or it is false; a rule is either applicable or it is not.

A Fuzzy datum's membership in a clause can be looked upon as how "deep" it is within the fuzzy subset. If a datum is not within the fuzzy subset, then its membership is zero. Zero and 1 represent definite certainties, while values between them represent intermediate certainties or possibilities. The intervening or middle values are attempts to represent the uncertainty of membership of a particular element in a Fuzzy subset.

For the purposes of this project each Fuzzy interval, based upon a clause of the Absolute Criterion, was divided into five separate and equal neighborhoods and each neighborhood was assigned a certainty or confidence value of 0%, 25%, 50%, 75%, or 100% which corresponded to the following values: 0.00, 0.25, 0.50, 0.75, and 1.00. In this project, interpretative interval is synonymous with Fuzzy interval or Fuzzy subset. This particular implementation of Fuzzy Logic created discrete interpretational or Fuzzy subset domains. The Fuzzy rule was then evaluated under the max/min rule of Fuzzy composition (16, 17). The evaluations of the Fuzzy rule could either be 0%, 25%, 50%, 75%, or 100%, which could correspond to the linguistic terms: inferior infarction not possible, consider inferior infarction, inferior infarction possible, inferior infarction probable, and definite inferior infarction . These would be the possible membership assignments of the data to the Fuzzy set, inferior infarction. This particular implementation of Fuzzy Logic is a multivalued logic rather than an infinitely valued logic; stepwise or discrete domains are used. Infinitely valued logic could be the result of using continuous fuzzy subsets or membership functions to ascribe membership of the data. Also, any final evaluation above a confidence of 0% was considered positive for the purposes of this project.

1.3.3.3 MAX/MIN Composition: A Fuzzy Inference Rule

The MAX/MIN rule of composition is the principle under which the Fuzzy rule of this project is evaluated. Appendix B illustrates how the MAX/MIN principle works. Essentially the principle treats the logical connectives of a Fuzzy rule in the following manner. An "AND" connective means that the minimum of the two clauses is taken. For example if the clause is: 0.3/A and 0.8/B, the evaluation is 0.3, which is the minimum of

A and B. The notation, 0.3/A means that the membership of a datum in clause A is 0.3. On the other hand, if the clause is: 0.3/A or 0.8/B, the evaluation is 0.8, which is the maximum of A or B. An "OR" implies that the maximum membership is taken. Appendix C explores this further with more in depth examples. Table 1 illustrates how the wave information is evaluated by the Fuzzy clauses into a final interpretation, by the following composition:

$$\mathrm{MAX}\,\{\ \min\,[\ \mathrm{Conf\_1},\ \mathrm{Conf\_2},\ \mathrm{Conf\_3}\ ],\ \mathrm{Conf\_4}\ \}.$$

Conf_n, represents the confidence in a particular clause determined by prior evaluation of the particular data by the clause of the Fuzzy Criterion. Finally, as an aid to the reader for a fuller understanding of how the different types of rules evaluate electrocardiographic data, Table 2 shows how Fuzzy rule evaluations differ from the evaluations of the Classical rules, the Absolute Criterion and the Relaxed Criterion. Sample electrocardiographic data are evaluated by each rule and the final interpretations are shown for each rule.

1.3.4 <u>Certainty for the Application of Each Rule</u>

Finally, for the purposes of the project, a basic assumption was approved for each criterion: each was applied with equal validity to the data, specifically, the confidence for the application of the Fuzzy Criterion to the data was equal to one.

TABLE 1

Illustrations on how the Fuzzy Criterion Evaluates the Electrocardiographic Wave Data

	Q-mag	R-mag	Conf_1	Conf_2	Conf_3	Conf_4	Result
a.	0	200	0.00	0.00	0.00	0.00	0.00 (no)
b.	0	400	0.00	1.00	0.00	0.00	0.00 (no)
c.	-50	399	0.50	0.00	0.75	0.00	0.00 (no)
d.	-65	250	0.75	0.25	0.25	0.00	0.25 (yes)
e.	-150	300	1.00	1.00	0.50	0.50	0.50 (yes)
f.	-150	610	1.00	0.00	1.00	0.50	0.50 (yes)
g.	-200	600	1.00	0.75	1.00	0.75	0.75 (yes)
h.	-200	810	1.00	0.00	1.00	0.75	0.75 (yes)
i.	-250	500	1.00	1.00	1.00	1.00	1.00 (yes)

This illustrates how the wave information is evaluated by the clauses of the Fuzzy Criterion into interpretative confidences. The confidences are then evaluated by the MAX/MIN composition rule in order to determine what the final evaluation or interpretation for inferior infarction is. Any result greater than or equal to 0.25 constitutes an inferior infarction. In a concise formula:

Result = MAX { MIN [Conf_1, Conf_2, Conf_3], Conf_4}.

TABLE 2

Example Interpretations by the Criteria

	Q-mag	R-mag	T abnormal?	Fuzzy	Absolute	Relaxed
a.	0	400	no	no	no	no
b.	-50	399	no	no	no	no
c.	-65	260	no	yes	no	no
d.	-70	270	no	yes	no	yes
e.	-80	300	no	yes	no	yes
f.	-76	350	no	no	no	no
g.	-76	350	yes	no	no	yes
h.	-150	610	no	yes	no	no
i.	-150	610	yes	yes	no	yes
j.	-200	600	no	yes	yes	yes
k.	-200	610	no	yes	no	yes
l.	-250	500	no	yes	yes	yes

The above table is representative of normal electrocardiographic wave information, which was evaluated by each of the criteria. The first three columns represent possible wave data (wave-triplets). The last three columns represent the interpretations by the criteria. A "yes" signifies an inferior infarction. A "no" interpretation signifies no infarction. A "yes" interpretation by the Fuzzy Criterion was any confidence greater than or equal to 0.25. The results point out some differences in the interpretative behavior of the criteria. Note in particular: c and d; f and g; h and i; j and k. Minor variations (due to noise) in the information near "crisp" or absolute boundaries can give rise to classification errors, especially in the Absolute Criterion.

The Relaxed Criterion did not include a clause that evaluated the R-wave magnitude.

CHAPTER 2

METHODS

2.1 Methodology of Patient Study I

This study (15) was undertaken to study the consistency or stability in electrocardiographic interpretations of serial electrocardiographic data by the Absolute Criterion and the Fuzzy Criterion. The physicians' interpretations of the electrocardiograms were used as a standard.

A set of 374 electrocardiographic records containing a compilation of the recorded magnitudes of electrocardiographic waves and their associated descriptions (modifiers) was collected and used to create a patient database. The records collected were limited to patients who had two or more computerized electrocardiograms during their hospital stay, i.e., serial electrocardiograms. The electrocardiograms were collected according to the Frank lead protocol. This particular study reanalyzed each patient's serially recorded electrocardiograms with the Fuzzy and Absolute Criteria for indications of inferior infarction. The interpretations of the criteria were based solely on the recorded magnitudes of the Q- and R-waves from the Y-lead of the Frank protocol from the patient records. The sequential sets or serially interpretational results from the two criteria were compared to the physicians' statements and diagnoses from their evaluations of the same electrocardiograms and the same patients. These statements or diagnoses had been stored with the patients' computerized medical records as "physician overread" statements.

2.2 Methodology of the Simulation Study

This study (18) was undertaken to examine the interpretational behavior of the different criteria under different levels of noise in a Monte Carlo simulation. The simulations distributed the wave magnitudes normally about a mean in order to model noise. The spread or distribution of the waves was proportional to the level of noise.

2.2.1 A Means of Studying the Effects of Gain on the Interpretational Behavior of the Fuzzy Rule

This study also looked at the effects of altering the Fuzzy subsets or interpretation intervals of the Fuzzy rule which, describe the membership relations of the Fuzzy rule clauses. These Fuzzy clauses were derived from the clauses of the Absolute Criterion. If the Fuzzy subsets or interpretational intervals were dilated (made larger), then the gain of the Fuzzy rule was increased; otherwise if the interpretational intervals were contracted (made smaller), the gain was decreased. Appendix D gives an illustration of what gain means in terms of the Fuzzy Criterion.

2.2.2 Conceptual Design of the Monte Carlo Study

The overall conceptual design of the simulation project is illustrated by Figure 4. The simulation study consisted of a group of simulation study

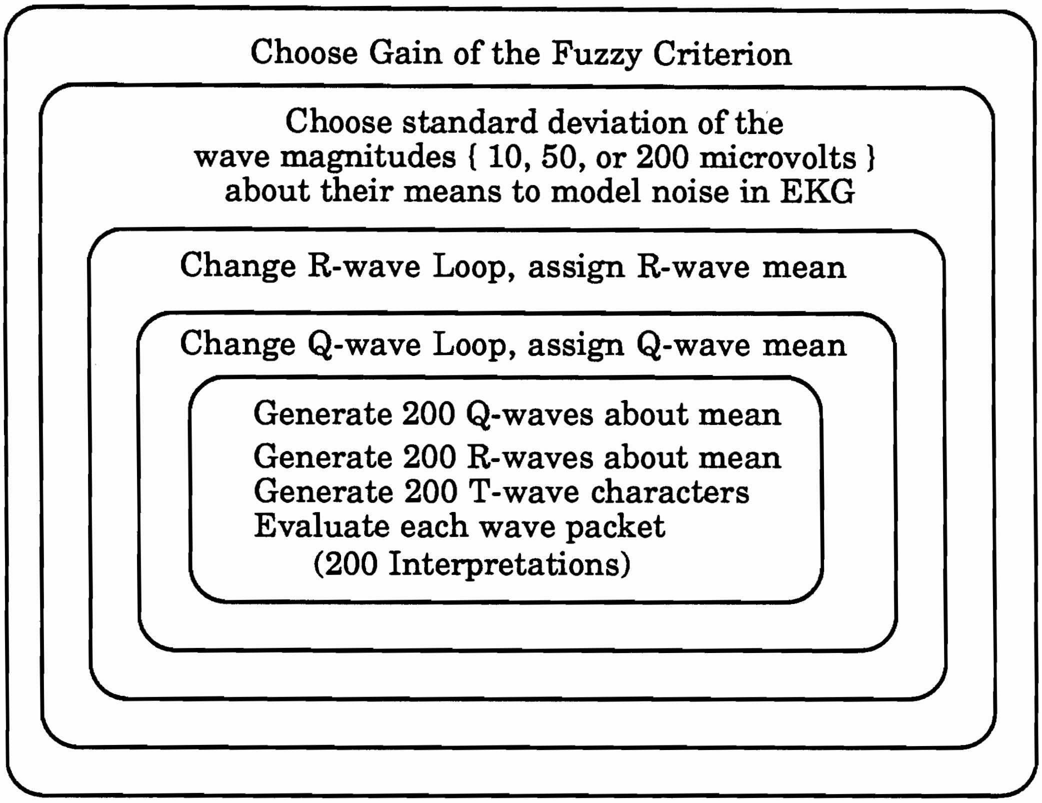

FIG. 4. Simulation Conceptual Structure. The above diagram illustrates the overall conceptual structure of the simulation study. The diagram implies a normal distribution of the Q- and R-waves about their mean magnitudes. Standard deviations of the normal distribution of the wave magnitudes were assigned for each simulation study. The t-wave character was randomly and equiprobably allowed to be either abnormal or normal.

sets. These simulation study sets were comprised of a group of simulations with the same data noise level and gain for the Fuzzy Criterion. Changing the gain alters the membership function with subsequent changes in the overall interpretative behavior of the rule.

2.2.2.1 Definition of a Simulation and
Wave Magnitude Constraints

Each simulation set consisted of a set of magnitudes for Q and R that had been generated about a set of means for both Q and R. The range of the R-wave means was 50 to 1000 microvolts, with 50 microvolt increments (steps) between each mean (viz. 50, 100, 150, . . . 1000 microvolts, i.e, the R range = [50 microvolts, 1000 microvolts] step 50 microvolts), and the range of the Q-wave means was -300 to 0 microvolts, with 50 microvolts increments between each mean (viz. -300, -250, . . . 0 microvolts, i.e., the Q range = [-300 microvolts, 0 microvolts] step 50 microvolts). Finally, a single simulation consisted of a group of wave-triplets generated under an equal level of noise (200 values each for Q, R, and T).

2.2.2.2 Data Set Description

This study was limited to interpreting simulated magnitudes of Q- and R-waves, and the character of the T-wave for the indication of inferior infarction. The T-wave was considered to be either normal or abnormal in character. The above electrocardiographic data were modelled and measured from the hypothetical Y-lead of the Frank protocol for the measurement and recording of an electrocardiogram.

2.2.2.3 VAX system and Random Number Generator

The simulation was implemented in VAX-11 FORTRAN, on a VAX 750 computer (Digital Equipment Corporation).

The general random number generator (MTH$RANDOM, a multiplicative congruential random number generator) used in this study was found in the Run-Time Library of routines for the VAX.

2.2.2.4 Simulation of Q- and R-waves

To simulate the Q-wave magnitudes, the R-wave magnitudes, and the T-wave character, three different (independent) random number arrays were generated for Q, R, and T. These arrays were generated using three different seeds with separate calls to the random number generator for each array. After the arrays of random numbers were generated for the Q, R, and T-waves, each array was used to generate either a wave magnitude for Q and R, or a normal or abnormal T-wave value or characteristic.

2.2.2.5 Generation of the Separate Random Number Array Elements for the Q- and R-waves

In the case of the Q - and R-waves, the simulation program distributed the magnitudes of the waves normally about the specified individual Q and R means and placed the resultant magnitudes into two individual arrays dimensioned for 200 elements, one magnitude array for Q and another for R. To do this, an algorithm found the sum of 12 consecutive random numbers to give an intermediate value, which was later converted into wave magnitudes distributed about a mean magnitude. The algorithm that follows was applied to the complete random number arrays of Q and R, which contained 12,000 random numbers each, the size needed to derive 200 magnitudes. This algorithm found the sum of each set of 12 consecutive random numbers and placed these sums into intermediate arrays, one for the Q-waves and one for the R-waves. The algorithm looked like this:

```
intermediate_value(j) =
    random_number(i) + random_number(i+1) +
    random_number(i+2) + . . . + random_number(i+12)
if not finished, get next set of 12-random numbers
else stop summing random numbers.
```

2.2.2.6 Algorithm for Forming a Normal Distribution of Q- or R-waves

The following algorithm took each intermediate value from the above algorithm and generated magnitudes normally distributed about an assigned mean for Q, which had been provided by the program.

```
Q_wave_magnitude(k) = Q_mean_magnitude +
    standard_deviation_in_Q_wave * [ intermediate_value(i) ]
```

This algorithm generated 200 magnitudes for Q about each mean assigned by the program. Values for the R-wave were generated in a like manner. Such a set of magnitudes, along with the T-wave information, comprised one simulation.

2.2.2.7. Noise in a Simulation Was Simulated by the Spread in the Distribution of the Q- and R-waves about a Mean

The "standard_deviation_in_Q_wave" (i.e., the variable corresponding to the standard deviation in the Q-wave) was used to model the level of noise in the Q-waves in an electrocardiogram. This quantitiy was proportional to the level of noise. In a like manner, the level of noise in the R-waves was modelled, with a value equal to the "standard_deviation_in_Q_wave." Hence, both wave magnitudes carried the same simulated noise level. Noise as used in this study was considered to be synonymous with electrical noise in the electrocardiogram, physiological noise in the electrocardiogram, variability in the patient clinical episode or other factors of uncertainty in the medical decision making process.

2.2.2.8 Generation of the T-wave Character

The character of the T-wave was generated from another independent array of random numbers. If the random number was greater than 0.5, then the T-wave was considered normal. However, if the random number was less than or equal to 0.5, then the T-wave was considered abnormal.

2.2.2.9 Wave-triplets: Conceptual Means of Representing the Data Elements Evaluated by the Rules

The values for the Q, R, and T-waves were associated into triplets. These wave-triplets were interpreted by the three criteria to determine if the data indicated inferior infarction. The three criteria are listed in

Appendix A.

2.3 Methodology of Patient Study II

The database of this particular study was similar in nature to that of the first patient study, although this database contained 251 patients instead of the 374. Patients with pacemakers had been removed.

2.3.1 Database Description

As with the first database, each patient in this second database also contained a Physician Diagnosis (Physician Overread) and electrocardiographic data, which included the magnitudes, and character of the Q, R, and T-waves from the Y-lead of the Frank protocol. As in the first study, the wave data were evaluated by the Absolute and Fuzzy Criteria to determine if there was an indication of inferior infarction. In addition, the Relaxed Criterion also evaluated the wave data and made use of the T-wave character in its interpretation process. Each interpretation by the criteria was compared to the results of the physicians' findings, which were stored as the Physician Overread statements.

2.3.2. True Positives, True Negatives, False Positives, and False Negatives Are Defined

If an interpretation by a criterion was indicative of an inferior infarction, then this was labelled a positive (or a "yes" interpretation for inferior infarction); otherwise, it was a negative (or "no") finding for inferior infarction. After the interpretation of an electrocardiographic record, the result was compared to that of the Physician Overread

(Physician Diagnosis). If the criterion's interpretation was positive and it agreed with the Physician, then it was a true positive interpretation (true because it agreed with the Physician's interpretation); otherwise, it was a false positive interpretation (because it did not agree with the Physician). On the other hand, if the criterion's interpretation was negative and this was in agreement with the Physician's diagnosis, then this was a true negative interpretation . Otherwise, it was a false negative interpretation. So, in this particular study, the Physician's diagnosis was considered "truth," by which the other criteria were compared as true positives, true negatives, false positives, and false negatives. From these determinations, the sensitivities, specificities and positive predictive values were calculated for each criterion. Figure 5 provides the definitions of these statistical quantities and details for how the quantities were calculated.

	Infarction (diseased)	No Infarction (not diseased)	ROW TOTALS
Positive (yes)	True Positives (TP)	False Positives (FP)	number of positives
Negative (no)	False Negatives (FN)	True Negatives (TN)	number of negatives
COLUMN TOTALS	number with infarctions	number without infarctions	Total in study

sensitivity = number of TPs / number with infarction
specificity = number of TNs / number without infarction
positive predictive value (ppv) = number of TPs / number of positives

FIG. 5. Format for the 2X2 Contingency Table. This format was used to calculate the sensitivities, specificities, and positive predictive values for each of the criteria in Patient Study II.

CHAPTER 3

RESULTS

3.1 Results from Patient Study I

The contingency tables in Figure 6 summarize the results of the first patient study (15). The numbers in each cell represent the interpretational results of the three criteria. The cells contain the number of unchanged interpretational patterns or interpretational patterns that underwent a change from one time sequential electrocardiographic record to another. For this particular study, a nonzero interpretation or a positive finding for inferior infarction by a physician was represented by a statement in the physician overread of inferior infarction, with any modifier, or significant inferior Q-waves. A zero interpretation or a normal electrocardiographic pattern or a negative finding for inferior infarction was represented by an absence of the above types of physician overread statements. A nonzero interpretation by the Fuzzy Criterion was an evaluation equal to a confidence greater than 0% (i.e., confidences equal to 25%, 50%, 75%, or 100%). A nonzero interpretation by the Absolute Criterion was a positive finding, i.e., the Absolute Criterion had an evaluation of 1 for inferior infarction.

Two sequential (serial) electrocardiograms were evaluated by each criterion. The serial results from the rule criteria and the physician each

	NO (0)	YES (1)	TOTAL
NO (0)	302	27	329
YES (1)	22	23	45
TOTAL	324	50	374

Absolute Criterion

	NO (0)	YES (1)	TOTAL
NO (0)	241	19	260
YES (1)	24	90	114
TOTAL	265	109	374

Physicians' Criteria

		NO	YES				TOTALS
		0%	25%	50%	75%	100%	
NO	0%	238	10	5	3	12	268
YES	25%	9	8	8	0	4	29
	50%	5	3	6	1	3	18
	75%	5	1	1	1	7	15
	100%	12	4	3	4	21	44
	TOTALS	269	26	23	9	47	374

Fuzzy Criterion

	NO (0)	YES (1)	TOTAL
NO (0)	238	30	268
YES (1)	31	75	106
TOTAL	269	105	374

Compiled
Fuzzy Criterion

FIG. 6. Results from Patient Study I. The results from Patient Study I are summarized in the tables above. A compiled Fuzzy table is included to aid the reader. In this compiled table, any confidence greater than 0% was considered a "yes." Otherwise it was considered a "no."

Patient Study I had the possible interpretational patterns: zero-to-zero, zero-to-nonzero, nonzero-to-nonzero, and nonzero-to-zero. If an interpretation did not indicate inferior infarction for one set of data and this interpretation did not change with the next set of time sequential data for the patient, then this was a zero-to-zero serial interpretational pattern. If there was no change in a nonzero interpretation from one data set to another, then this was a nonzero-to-nonzero pattern. If the intepretation for a particular data set was indicative of inferior infarction and the next time sequential data set was not indicative inferior infarction, then this was a nonzero-to-zero pattern. If the interpretation for a data set was no indication of inferior infarction and the next set data was interpreted as indicative of inferior infarction, then this was a zero-to-nonzero pattern.

formed the following serial interpretational patterns. For the Physicians' Criteria and Absolute Criterion, these patterns were: no inferior infarction to no inferior infarction (a zero to zero pattern), yes inferior infarction to yes inferior infarction (a positive to positive pattern), yes inferior infarction to no inferior infarction (a positive to zero pattern), and no inferior infarction to yes inferior infarction (a zero to a positive pattern). In a similar manner, the Fuzzy Criterion serial interpretational patterns were formed. However, they consisted of a confidence value to a confidence value, e.g., a 25% to 25%, or a 0% to a 75% pattern. These patterns were then grouped into: positive to positive (greater than 0% to greater than 0% patterns), zero to zero (0% to 0% patterns), positive to zero (greater than 0% to 0% patterns), and zero to positive (0% to greater than 0% patterns) to facilitate comparison to the Absolute Criterion and Physicians' Criteria results.

This study was not undertaken to determine the absolute truth for the interpretations by the criteria. Instead, this study was an attempt to examine the interpretational behavior, and consistency (stability) in the interpretation of serial electrocardiographic records by the Fuzzy Criterion in relation to the other criteria. The results from the Physicians' Criteria were employed as a relative metric for the comparisons in behavior between the Absolute and Fuzzy Criteria. The physicians' interpretations also served as the basis to compare the consistency of the criteria in relation to the presence of noise in the electrocardiographic data. Some preprocessing/filtering and analysis occurred with the data for feature extraction (such as magnitudes, and T-wave character) before the data had been entered into the record by the automated electrocardiographic algorithms or possible manual processes. Even though these processes should reduce the noise in the electrocardiographic data, it is possible that this was not done in every case. If the data analysis package recorded magnitudes which did not reflect the actual electrocardiographic event, then the criteria could make incorrect interpretations. The Absolute Criterion and the Fuzzy Criterion results could in some circumstances have increased the uncertainty and made classification errors for the presence of inferior infarction. This could lead to inconsistencies in the serial interpretational patterns. The criteria only analyzed one set of data per time period. Data that were collected over this time period were compiled into the recorded magnitudes of each electrocardiographic record by the electrocardiographic feature extraction algorithms. Significance of features or patterns is not an issue in such data collection methods. The physician, on the other hand, could view the complete electrocardiogram, and choose the significant patterns. The physician could then base interpretations on the patterns he or she chose.

Interesting possibilities are suggested by the results. For example, the Absolute Criterion exhibited a more conservative interpretational pattern than the Fuzzy Criterion as suggested by the zero to zero interpretational patterns. The Absolute Criterion had a greater number of zero to zero patterns (implying a resistance to change a previous zero interpretation to one that is nonzero with new information that may be more indicative of an inferior infarction) whereas the tally for the Fuzzy Criterion was not substantially less than the Physicians' Criteria: 302 for the Absolute Criterion, 241 for the Physicians' Criteria, and 238 for the Fuzzy Criterion. When the patterns are positive to positive, the Fuzzy Criterion again more closely approximated the Physicians' Criteria and the Absolute Criterion appeared, as in the previous result, to be more conservative, as well as less stable, than either of the other two criteria: 23 for the Absolute Criterion, 90 for the Physicians' Criteria, and 75 for the Fuzzy Criterion. The remaining results suggest that the Fuzzy Criterion may be more aggressive and prone to inconsistent behavior for the remaining interpretational patterns . For example neither the Fuzzy or the Absolute Criteria resemble the pattern of the Physicians' Criteria for the zero to nonzero patterns. Each appears more prone to change an interpretation from zero to nonzero than the Physicians' Criteria, with the Fuzzy Criterion slightly more so: 27 for the Absolute Criterion, 19 for the Physicians' Criteria, and 30 for the Fuzzy Criterion. The remaining pattern, nonzero to zero patterns, again suggests that the Fuzzy Criterion is not as stable as the Absolute Criterion under these circumstances since it tends to change its original interpretation more often than the other criteria. Yet the range for this particular pattern is the least among the four, and the Physicians' Criteria are between either of the other criteria, which together may indicate a more stable status for the Fuzzy and Absolute Criteria than the differences between the results indicate: 22 for the Absolute Criterion, 24 for the Physicians' Criteria, and 31 for the Fuzzy Criterion.

3.2 Results from the Simulation Study

Figures 7, 8, and 9 compare the effect of noise on the interpretative behavior for each criterion. The gain of the Fuzzy Criterion was equal to one in each figure of this group. The vertical axis represents the average number of positive interpretations for each simulation and the horizontal axis represents the means (i.e., the variable "Q_mean_magnitude" in the aforementioned equation) for the distributions of the Q-waves in each simulation.

When the noise (Figure 7) was represented by a standard deviation of 50 microvolts in the distributions of the Q- and R-waves, there appears to be little, if any, overall dissimilarity in the interpretative profiles of the Fuzzy and Relaxed Criteria. This was considered to be a normal level of noise in this simulation study. However, the Absolute Criterion profile suggests that in those simulations where the values of the Q-waves are in the region of -250 microvolts, there is a tendency for this particular criterion to reflect more interpretations that are negatives (possibly more false negatives) as compared to the profiles of the Fuzzy and Relaxed Criteria. On the other hand, near the regions of -100 or -50 microvolts, the Fuzzy and Relaxed Criteria tend to reflect a greater number of positive interpretations (perhaps a greater number of false positives) as compared to the profile of the Absolute Criterion. Noise in the electrocardiogram, imprecision in how the magnitudes are measured by the computer algorithm, patient variability, or other sources of noise could contribute to these types of results when data from clinical electrocardiograms are analyzed by the criteria.

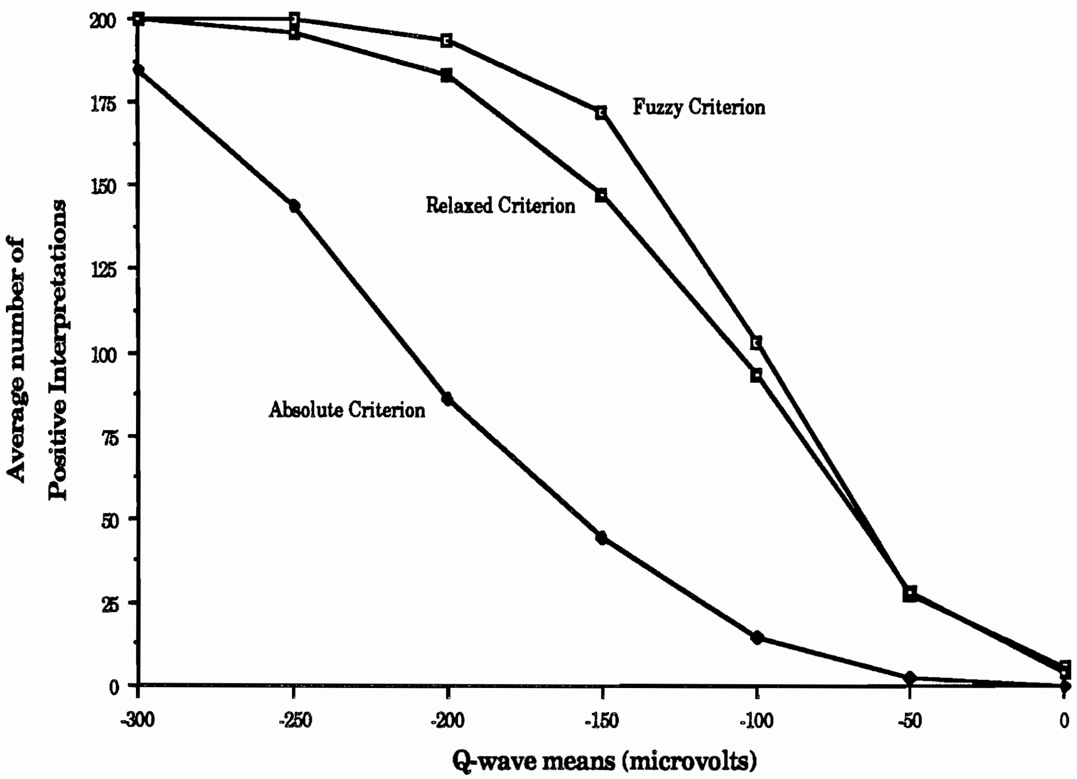

FIG. 7. Positive Interpretational Behavior of the Criteria, Noise = 50 microvolts. This amount of simulated noise was considered normal. Gain = 1.00.

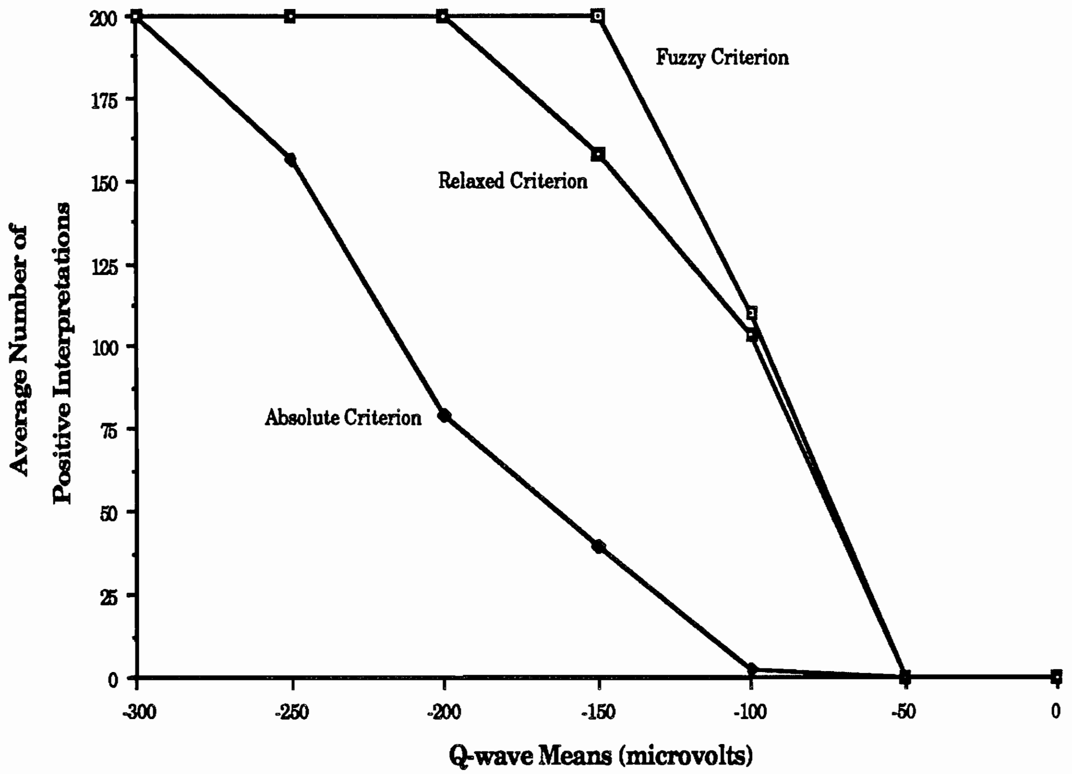

FIG. 8. Positive Interpretational Behavior of the Criteria, Noise = 10 microvolts. This amount of simulated noise was considered to have been 1/5 the normal level. Gain = 1.00.

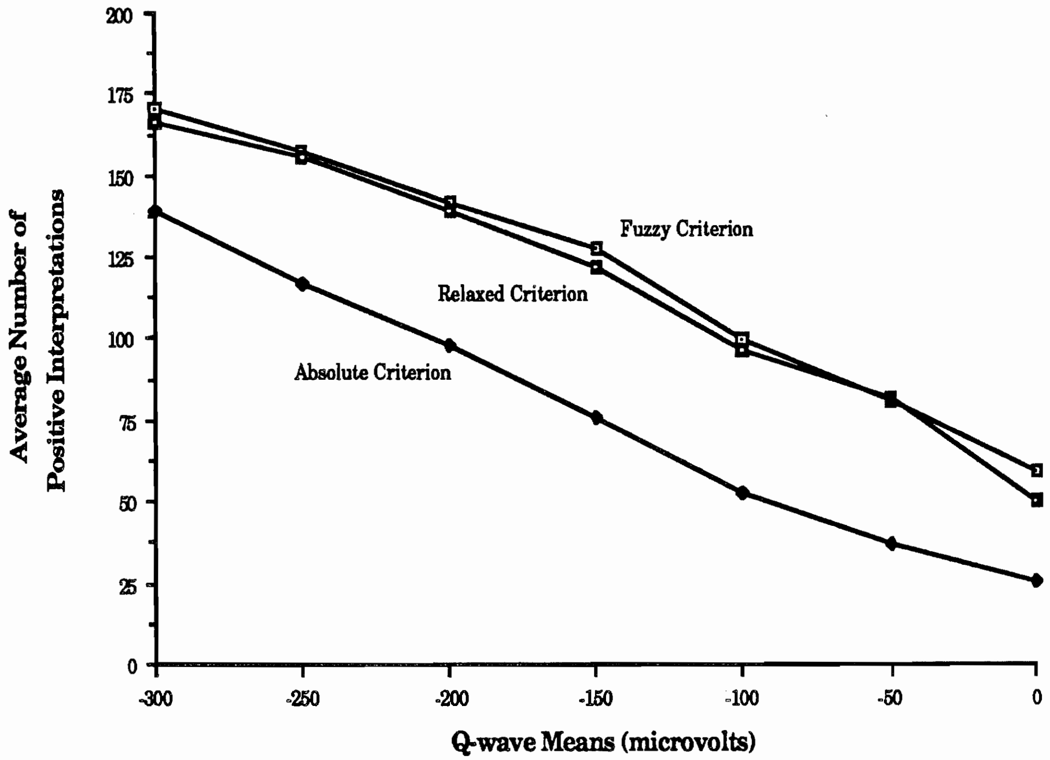

FIG. 9. Positive Interpretational Behavior of the Criteria, Noise = 200 microvolts. This amount of simulated noise was considered to have been four times greater than the normal level. Gain = 1.00.

When the noise level (Figure 8) was represented by a standard deviation of 10 microvolts (which was considered to be a low level of noise in this simulation study) in the distributions of the Q- and R-waves, thereagain appears to be little, if any, dissimilarity between the profiles of the Fuzzy and Relaxed Criteria. Due to the low level of noise (i.e., "tighter" distributions of the Q- and R-waves about their means) and the inherent relaxation of the boundaries in the Relaxed Criterion, specifically the third clause (if Q-wave is less than or equal to -150 microvolts then inferior infarction), the Relaxed Criterion interprets all wave-triplets from distributions of Q-waves with means less than or equal to -200 microvolts as yes interpretations for inferior infarction (positive interpretations). Likewise, due to the tighter distributions of the simulated wave magnitudes and the interpretation intervals (or fuzzy subsets) of the Fuzzy Criterion, especially the third clause (confidence of inferior infarction is 25% or greater if the Q-wave is less than or equal to -100 microvolts), the Fuzzy Criterion's interpretations are positive (yes interpretation for inferior infarction) for all wave-triplets from distributions of Q-waves with means less than or equal to -150 microvolts. So the Relaxed Criterion has extended its "all positive" interpretations to Q-waves distributed about means less than or equal to -200 microvolts and the Fuzzy Criterion has extended its "all positive" interpretations to Q-waves distributed about means less than or equal to -150 microvolts compared to the ranges established in the profiles with the noise level at 50 microvolts. The Absolute Criterion's interpretations in the Q-wave region of -250 microvolts reflect a slightly less conservative interpretative behavior with this lower level of noise than when the level of noise was equal to 50 microvolts (Figure 7). On the other hand, since the Fuzzy and Relaxed Criteria have extended their respective "all positive" Q-wave interpretation ranges, the two criteria reflect a more aggressive interpretative behavior than the behavior explicated with the level of noise considered to be normal, yet higher than the 10 microvolts in this simulation.

When the noise level was increased to a standard deviation of 200 microvolts (Figure 9), which was considered to be a high level of noise in this simulation study, the distributions for the magnitudes of the Q- and R-waves became more widely dispersed about their means used in this study. The Fuzzy and Relaxed Criteria appear to have similar profiles and the "all positive" interpretative behavior has vanished from the profiles of these two criteria. This spread in the distributions of the magnitudes was caused by the higher level of noise; 200 microvolts in this case. The Absolute, Fuzzy, and Relaxed Criteria all tended to infer more of the simulated magnitudes of the Q-waves near the means of -50 and 0 microvolts than in simulations of lower noise as representing inferior infarctions. Each criteria at this end of the Q-spectrum tended to be less conservative, i.e., the Fuzzy and Relaxed Criterion tended to be more aggressive in their interpretational behaviors, while at the opposite extreme, all three criteria tended to be more conservative, which is reflected in their average number of positive interpretations. The Absolute appears to be the most conservative.

However, when the distributions for the magnitudes of the Q-waves were centered around means of -250 microvolts or less, the Absolute Criterion tends to interpret these magnitudes as not representing inferior infarctions, whereas the Fuzzy and Relaxed Criteria do, when compared to the results of those simulations where the noise was represented by 50 and 10 microvolts standard deviations in the distributions for the magnitudes of the Q- and R-waves about their means. Even so, the Absolute Criterion in this region tends to interpret a greater number of negatives, whereas the Fuzzy and Relaxed Criteria's interpretations tend to reflect a greater number of positives, when the noise level is increased to the level of 200 microvolts.

Figures 10, 11, and 12 represent how noise affects (or interferes with) the consistency of the interpretations for inferior infarction in each criteria. The horizontal axis represents the means of the normal distributions for the magnitudes of the Q-waves in each simulation. The vertical axis represents the standard deviations for the number of positive interpretations for the criteria in each simulation, i.e., the standard deviations in the average number of positive interpretations for each R-wave simulation which were determined from the entire range of possible R-wave means for one Q-wave mean simulation. The gain of the Fuzzy Criterion in this group of figures was equal to one.

Figure 10 was based on simulated data with a noise level of 50 microvolts. The Relaxed and Fuzzy Criteria are influenced to a lesser degree in the spread of the number of positive interpretations, which is

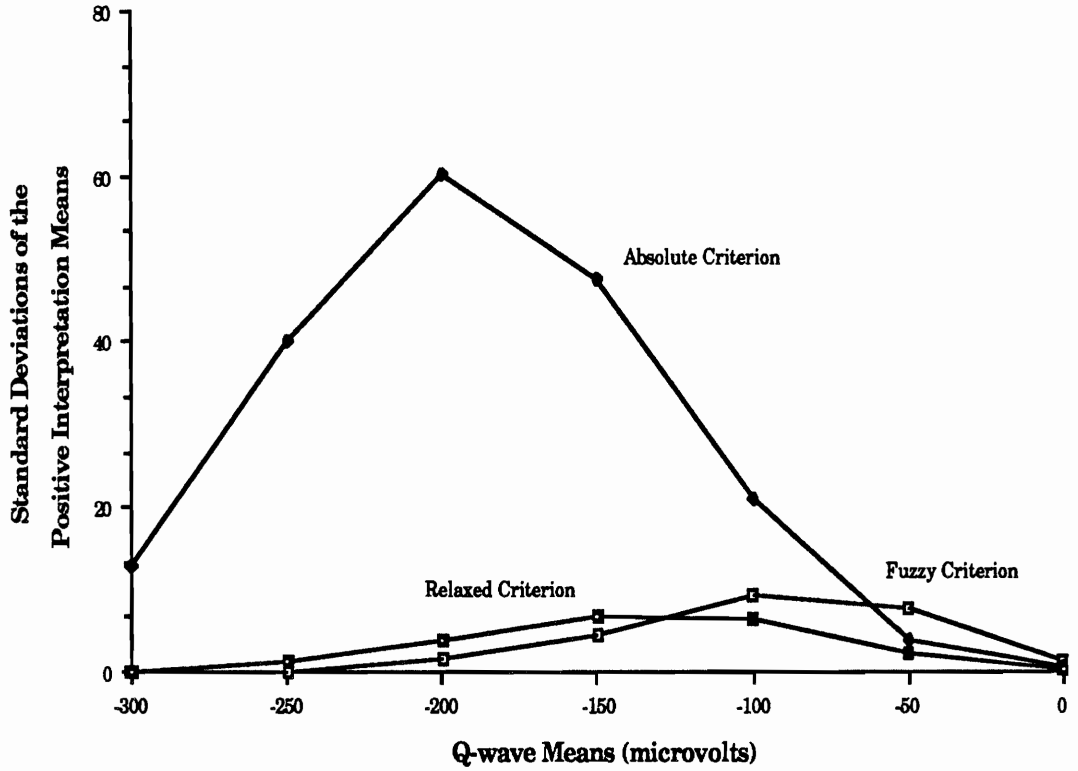

FIG. 10. Stability Profiles of the Criteria, Noise = 50 microvolts. This was considered to be a normal amount of noise. Gain = 1.00.

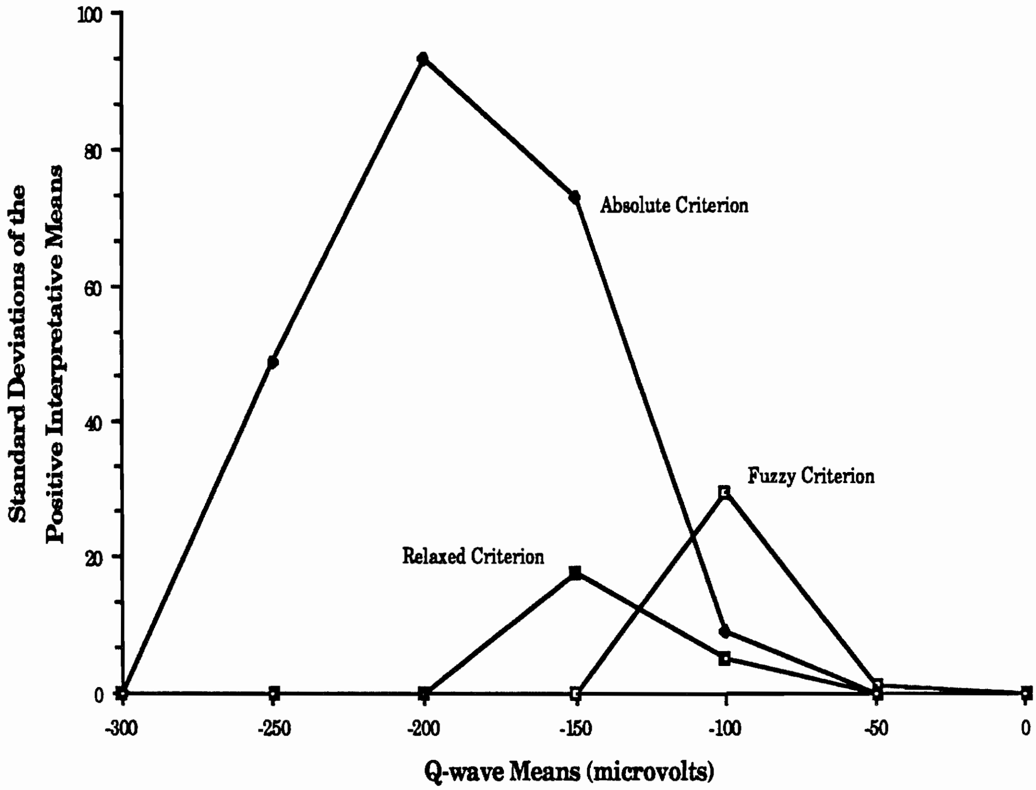

FIG. 11. Stability Profiles of the Criteria, Noise = 10 microvolts. This was considered to be 1/5 the normal amount of noise. Gain = 1.00.

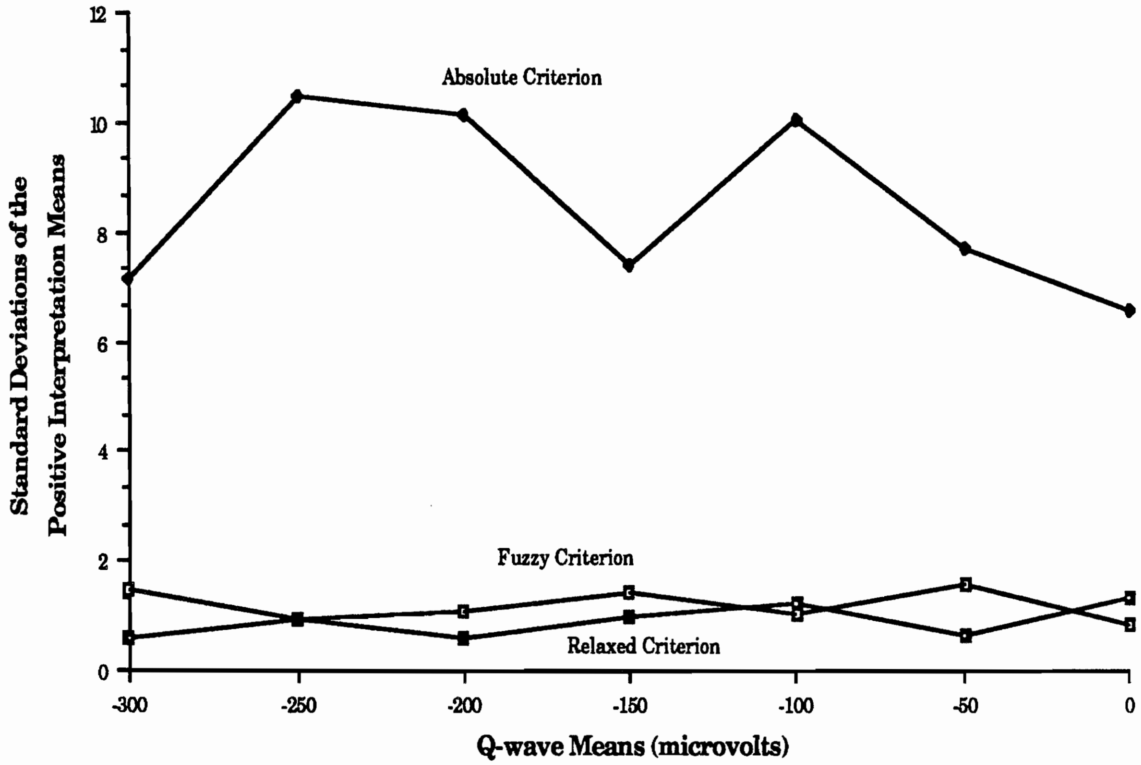

FIG. 12. Stability Profiles of the Criteria, Noise = 200 microvolts. This was considered to be four times the normal amount of noise. Gain = 1.00.

reflected in the smaller standard deviations over the Q-wave range of -300 to -100 microvolts, than the Absolute Criterion. However, the clauses which place restrictions (clause two: if Q-wave magnitude is less than -0.25 * R-wave magnitude; and clause three: R-wave magnitude greater than or equal to 400 microvolts) on the R-wave and compare it to the Q-wave magnitude are responsible in large part for the inconsistency or instability in the interpretations in the Q-wave region of -300 to about -50 microvolts. A greater standard deviation for a particular Q-wave mean implies a greater inconsistency or instability at the criterion's interpretative behavior. A smaller deviation may imply that the criterion is less influenced by noise. For example, the larger standard deviations for the Absolute Criterion in the -250 microvolt range of the Q-wave reflect the inconsistency or a larger variation in the number of negative or positive interpretations in a particular simulation set. From the figure it is evident that the Fuzzy and Relaxed Criteria are less prone to interpretational instability in this region of the Q-wave (brought about by noise and the R-wave clauses), with this level of noise, because of their lower Q-wave thresholds (as in the case of the Relaxed Criterion) or use of Fuzzy subsets or interpretative intervals and the MAX/MIN rule of composition (as in case of the Fuzzy Criterion).

In Figure 11, the noise level has been reduced to 10 microvolts. The inconsistency in the number of positive interpretations for inferior infarction has increased for all three criteria, with the Absolute Criterion exhibiting the largest standard deviation in the -250 to -150 microvolts range. As in shown in Appendix A , the "Q-wave less than -0.25 * R-wave and R-wave greater than or equal to 400 microvolts" clauses are responsible for this result, since the Q wave less than -250 clause did not influence the result of the final interpretations. The rise in the standard deviations of the Relaxed Criterion in the -150 microvolt region was also caused by clauses two and three (as in the Absolute Criterion) and clauses five and six which relate the Q-wave magnitude and the T-wave character (a randomly equiprobable result between normal or abnormal T-wave character) in this simulation study. The Fuzzy Criterion also exhibits a rise in its interpretational inconsistency in the number of positive interpretations since there is a larger standard deviation (standard deviation of approximately 30) in the -100 microvolt range. This is caused by the presence of 25% confidence interpretations for the third clause in conjunction with "tight" distributions for the Q-wave magnitudes about their different means (This results from inconsistencies in the evaluations of the second and third clauses, along with R-wave inconsistencies).

Figure 12, the standard deviations for the number of positive interpretations for inferior infarction have decreased to less than 12 for each criterion. The Fuzzy and Relaxed Criteria profiles are very similar to each other and are lower on the vertical scale than the Absolute Criterion. The Absolute Criterion achieves its variation in the standard deviations for the same reasons as mentioned in Figures 7 and 8. The reason that the criteria had a decrease in their profiles of the standard deviations was due to the fact that the spread or distributions of the Q- and R-waves was so great that no matter what the simulated wave magnitudes were, the distributions contained a substantial number of large and small magnitudes so that at each Q-wave mean, the ratios of the number of large to small wave magnitudes, were consistent for each simulation within a simulation set.

Figures 13 and 14 show how altering the gain from a gain equal to one affects the interpretative behavior of the Fuzzy Criterion. The noise level for each figure was 50 microvolts. The gain was altered as in Figure 13 by using values between 0 and 1.5. Gains greater than 1 brought about a concomitant increase in the number of positive interpretations, and the Q-wave range over which the "all positive" interpretations were found when the gain was equal to one was extended from -200 to -150 microvolts. An increase in the gain brought about a more aggressive interpretational behavior. On the other hand, as the gain was lowered from one, the interpretative profile reflected that the Fuzzy Criterion became more conservative in the number of positive interpretations. In addition, the "all positive" behavior disappeared as well. In fact when the gain is allowed to go to zero, the Fuzzy Criterion becomes the Absolute Criterion. This is shown in Figure 13, as represented by the curves labelled with gain = 0. The blank square represents the Fuzzy Criterion, which overlays the solid line which represents the Absolute Criterion. Table 3 shows a point by point comparison which also illustrates this result.

In Figure 14, the effect of gain on the consistency for the interpretations in each simulation set is demonstrated, with the noise level equal to 50

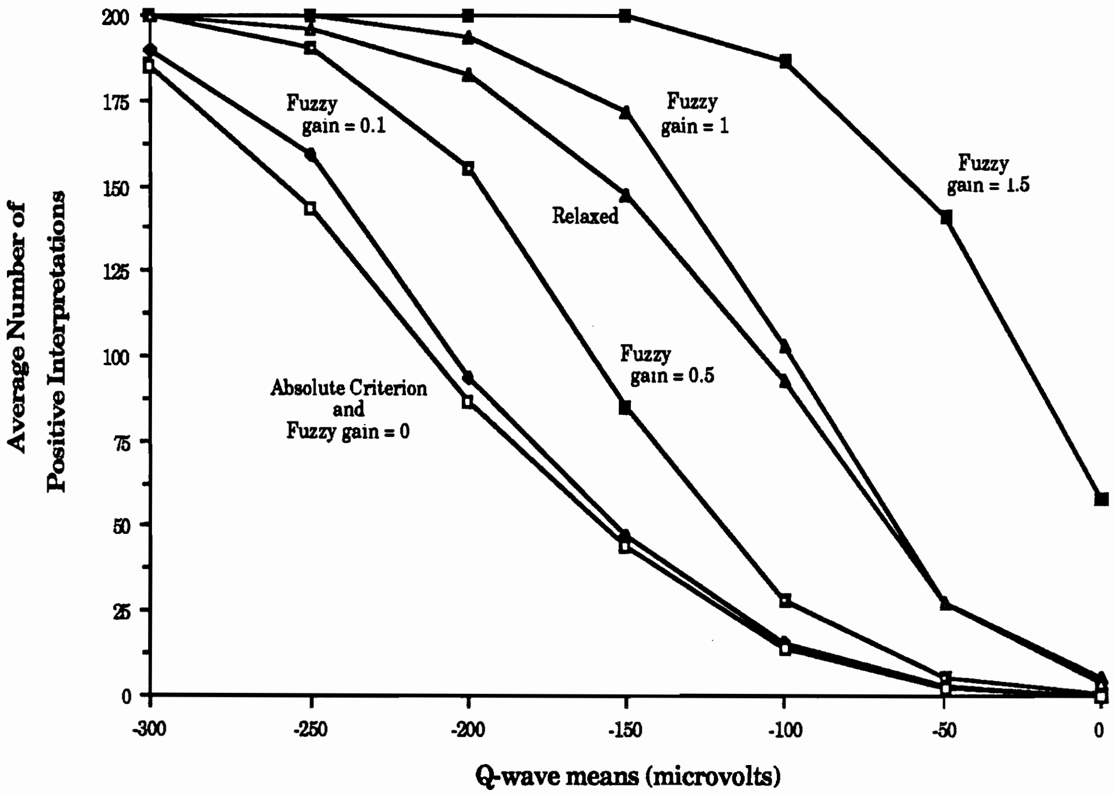

FIG. 13. How Gain Affects the Interpretational Behavior of the Fuzzy Criterion. Noise = 50 microvolts.

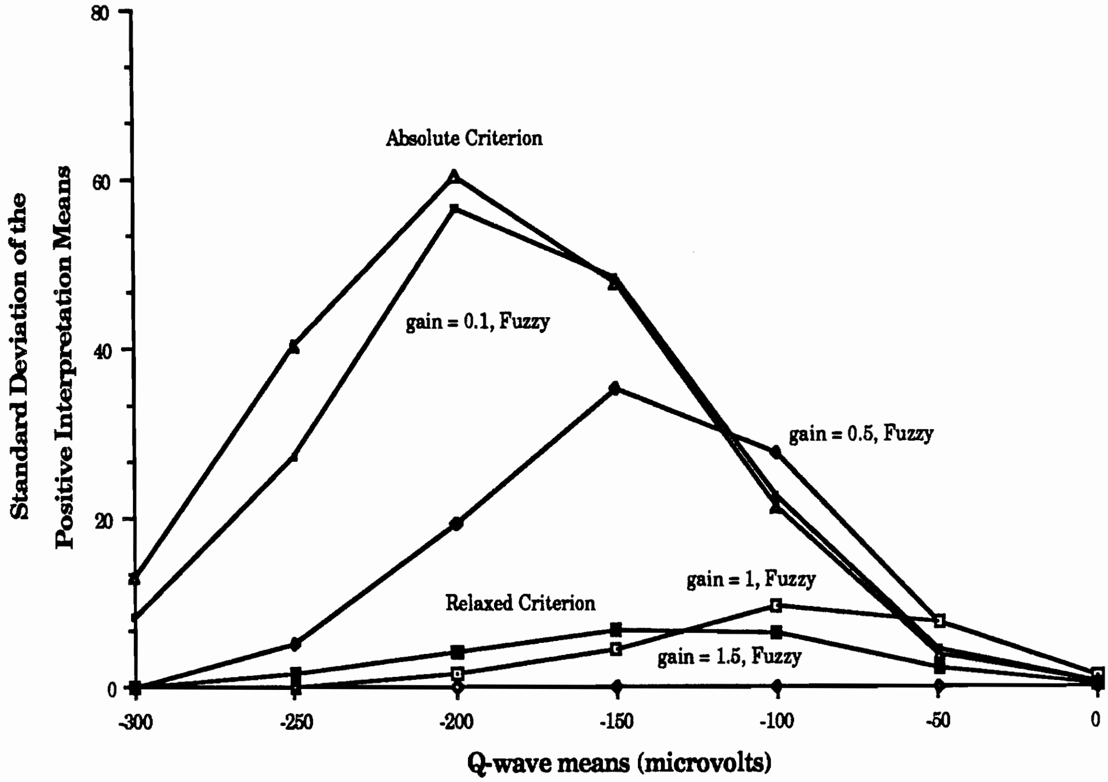

FIG. 14. How Gain Affects the Stability Profile of the Fuzzy Criterion. Noise = 50 microvolts. The Fuzzy Criterion, gain = 1.5 is coincident with the horizontal axis.

TABLE 3

Data for Fuzzy Criterion when the Gain = 0 versus
Data for the Absolute Criterion

Q-Wave Means: (microvolts)	Positive Interpretation Means:		Standard Deviation of the Positive Interpretation Means:	
	Fuzzy	Absolute	Fuzzy	Absolute
0	0.2	0.2	0.52	0.52
-50	2.4	2.4	3.93	3.93
-100	14.2	14.2	21.20	21.20
-150	43.9	43.9	47.53	47.53
-200	86.3	86.3	60.36	60.36
-250	143.5	143.5	40.22	40.22
-300	184.7	184.7	13.01	13.01

The data presented for the positive interpretative means for the Fuzzy Criterion when the decision interval has been contracted to a single point, or "crisp" boundary, are the same as that of the Absolute Criterion. The standard deviations of the positive interpretative means are the same; hence both criteria have the same stability profile. They are equally stable with respect to noise.

The standard deviation of the wave measurements for this simulation was 50 microvolts.

microvolts. With gain values greater than one, the standard deviation is zero, since the size of the interpretative intervals (Fuzzy subsets) has been extended, thus "masking" or over "filtering" the presence of noise and the information itself, in the data. Consequently the Fuzzy Criterion exhibits a more stable profile, although this may not be beneficial in the interpretative environment. As the gain is decreased from one, this "masking" or "filtering" effect for the gain is weakened, perhaps with beneficial results, and as the gain becomes zero the stability of the Fuzzy Criterion approaches that of and overlays the profile of the Absolute Criterion. The second patient study will explore the possible beneficial results of altering the gain with respect to sensitivity and specificity.

3.3 Results from Patient Study II

Figure 15 represents the overall results from the patient study of all three interpretative criteria. The data from each criteria are represented in terms of true positives (tp), true negatives (tn), false positives (fp), and false negatives (fn). The sensitivities, specificities, and positive predictive values (ppv) for each criterion are shown in Table 4. In each, the Fuzzy Criterion's results were determined with the gain equal to one.

Examining Figure 15, it is apparent that the Absolute Criterion has interpreted the greatest number of true negatives (437 out of a possible 457). The Relaxed Criterion has interpreted 412 out of a possible 457, and the Fuzzy Criterion has interpreted the least, with 403 out of a possible 457.

From Table 4, the specificities reflect these results with the Absolute

	Infarction (diseased)			Without Infarction (not diseased)			Row Totals		
	Abs	Rel	Fuz	Abs	Rel	Fuz	Abs	Rel	Fuz
Positive (yes)	53	134	120	20	45	54	73	179	174
Negative (no)	123	42	56	437	412	403	560	454	459
Column Totals	176	176	176	457	457	457	633	633	633

FIG. 15. Contingency Table for the Criteria, Patient Study II. This table shows the results in terms of true positives, false positives, true negatives, and false negatives of the second patient study. Gain for the Fuzzy Criterion was equal to 1.0. Abs represents the Absolute Criterion, Rel represents the Relaxed Criterion, and Fuz represents the Fuzzy Criterion.

TABLE 4

Sensitivity, Specificity, and Positive Predictive Values for Patient Study II

	Absolute	Relaxed	Fuzzy
Sensitivity	0.30	0.76	0.68
Specificity	0.96	0.90	0.88
Positive Predictive Value	0.73	0.75	0.69

This table shows the sensitivities, specificities, and positive predictive values for the three criteria from Patient Study II. The gain for the Fuzzy Criterion was 1.00.

Criterion having the highest specificity (0.96), followed by the Relaxed Criterion (0.90), then the Fuzzy Criterion (0.88).

In terms of true positives, the Relaxed Criterion achieved the highest number of interpretations, with 134, followed by the Fuzzy Criterion with 120 true positives, and then the Absolute Criterion with 53 true positives. In terms of sensitivity, the Relaxed Criterion had the highest score with 0.76, followed by the Fuzzy Criterion (0.68) then the Absolute Criterion (0.30).

In terms of sensitivity, the Relaxed Criterion appears to out perform either of the other two criterion. The Fuzzy Criterion is 0.04 points less than the Relaxed Criterion and more than twice that of the Absolute Criterion. However, when the specificities are compared, the Fuzzy Criterion has the lowest value (0.88).

Lastly, the positive predictive value for the Relaxed Criterion (0.749) was the highest of the three criteria, followed by the Absolute Criterion (0.726), then the Fuzzy Criterion (0.690). The overall positive predictive values for the criteria obscure how the criteria compare with each other since the positive predictive value is the ratio of true positives to the sum of the true positives and false positives. When the number of true positives and false positives of the Absolute and Fuzzy Criteria are compared, the Absolute Criterion interpreted less than half of the false positives that the Fuzzy Criterion did, i.e., the Absolute had 20 false positives and the Fuzzy had 54 false positives, which is reflected in the lower specificity of the Fuzzy Criterion. However, the Fuzzy Criterion counted 120 true positives out of a possible 176, which was more than twice the number that the Absolute Criterion interpreted (53 true positives). This was reflected in the higher sensitivity for the Fuzzy Criterion compared to the Absolute Sensitivity. This could be of important clinical significance where sensitivity is more important than specificity.

Table 5 is the compilation of the different sensitivities, specificities, and positive predictive values for the Fuzzy Criterion when different gains were used. Included in this table are the sensitivities, specificities, and positive predictive values for the Fuzzy Criterion.

In general, as the gain is increased, the sensitivity increases and the specificity decreases. In this case the Fuzzy Criterion begins to behave as the Absolute Criterion, and with the gain equal to zero, the Fuzzy Criterion becomes basically the Absolute Criterion, since the Fuzzy Criterion's specificity and sensitivity have become that of the Absolute Criterion, i.e., 0.96 for the specificity and with sensitivities of 0.30 and 0.31 for the Absolute and Fuzzy Criteria, respectively. The Fuzzy Criterion had one true positive interpretation different from the Absolute Criterion because the Fuzzy reads **less than or equal** -250 microvolts in clause three instead of **less than** -250 microvolts as the Absolute Criterion does. When the gain for the Fuzzy Criterion was equal to one in the simulation study, the behavior profile matched exactly that of the Absolute Criterion, as did the interpretative consistency profiles under the different levels of noise.

As mentioned earlier, as the gain is increased, the sensitivity increases, but does not reach one because the interpretative parameters or

TABLE 5

Fuzzy Rule: Effect of Gain on the
Sensitivity, Specificity, and Positive Predictive Values

Fuzzy Gain	Fuzzy Sensitivity	Fuzzy Specificity	Fuzzy Positive Predictive Value
0.00	0.31	0.96	0.730
0.25	0.34	0.95	0.732
0.50	0.41	0.95	0.745
0.60	0.47	0.94	0.759
0.75	0.56	0.93	0.754
1.00	0.68	0.89	0.698
1.50	0.86	0.62	0.469
1.60	0.90	0.48	0.401
1.70	0.93	0.38	0.366
1.75	0.93	0.38	0.366
2.00	0.93	0.38	0.366
5.00	0.93	0.38	0.366

Classical Rules: Listing of Sensitivities, Specificities, and PPV.

Absolute Sensitivity = 0.30	Relaxed Sensitivity = 0.76
Absolute Specificity = 0.96	Relaxed Sensitivity = 0.90
Absolute PPV = 0.726	Relaxed PPV = 0.749

This table compares the sensitivities, specificities, and positive predictive values of the Fuzzy Criterion as the gain is changed from 0.00 to 5.00. Above a gain of about 1.70, no change occurs in the Fuzzy Criterion in its interpretative behavior. The sensitivities, specificities, and positive predictive values for the Classical rules are included for comparison.

boundaries remain fixed. Also, many HELP wave magnitude sets utilized in this study had Q-wave and R-wave magnitudes that were not indicative of inferior infarction, no matter what gain was chosen for the Fuzzy Criteria.

In Figure 16, the frequency for the Fuzzy Criterion's positive predictive values, sensitivities, and specificities are plotted against the different gains used in the patient study. Also plotted are lines representing the sensitivities, specificities, and positive predictive values from the Absolute and Relaxed Criteria (which are invariant under fuzzy gain). The sensitivity does not vary substantially as the gain is changed near the value of 0.5. This explains the behavior of the positive predictive value near gains of one, since it is the ratio of the number of true positives to the number of true positives plus the number of true negatives. The positive predictive value reflects the fast increase in the number of true positives and the slow change in the number of true negatives in this region of gain.

Figure 17 is the condensation of the different specificities and sensitivities of the Fuzzy Criterion with the different gains into an receiver operator characteristic curve, an ROC-curve (2, 19). Also plotted are the lines that represent the sensitivities and specificities of the Absolute and Relaxed Criteria. Lines are used since the sensitivities and specificities of these two criteria remain invariant when the gain is altered in the Fuzzy Criterion.

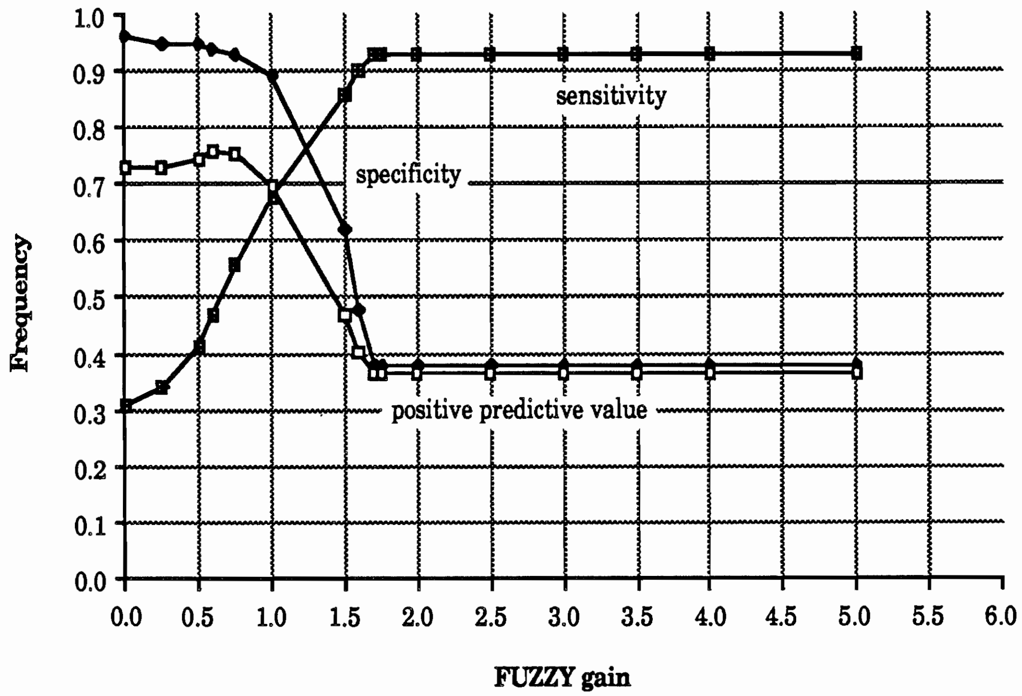

FIG. 16. The Effects of Gain on the Sensitivity, Specificity, and Positive Predictive Values of the Fuzzy Criterion.

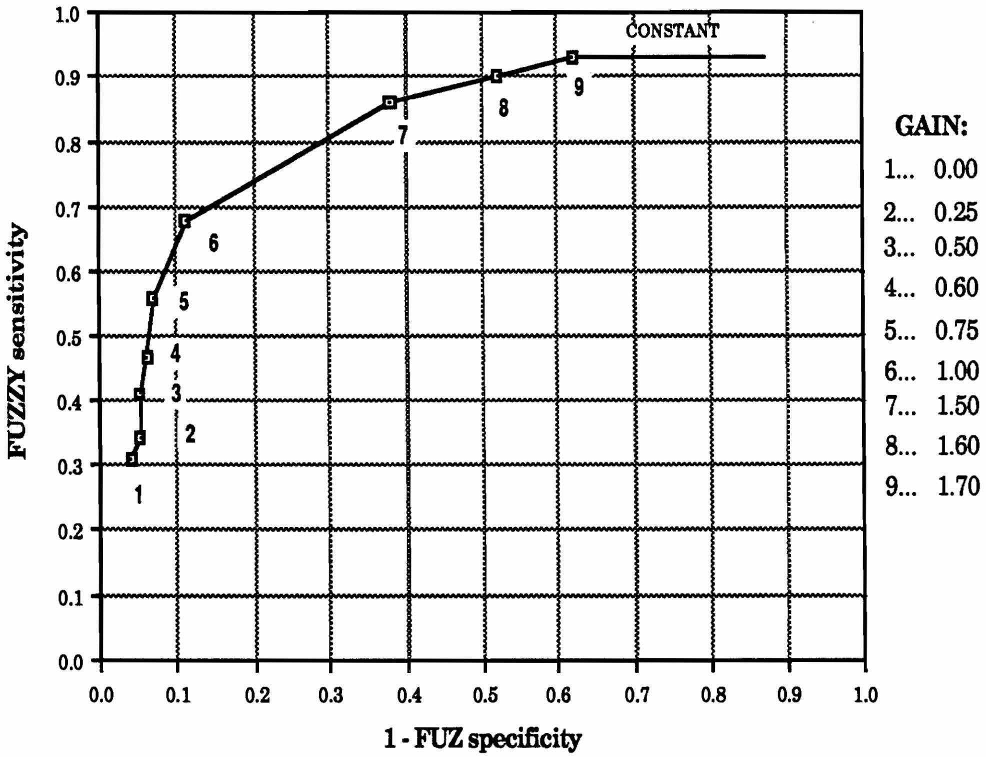

FIG. 17. ROC-curve for the Fuzzy Criterion. Each number refers to the gain at which the sensitivity and 1- specificity values were determined.

CHAPTER 4

CONCLUSIONS

4.1 Introduction

The three different studies covered in this project were performed to determine if a Classical rule that has been transformed directly into a Fuzzy rule better approximates the interpretational behavior of the physician, either in the interpretational patterns of serial electrocardiographic information, in terms of sensitivities/specificities, or interpretational stability in relation to noise. The first patient study illustrated the serial interpretational consistency of the Physicians' Criteria, Absolute Criterion, and the Fuzzy Criterion, and gave indications of the type of interpretational behavior that might be expected from the criteria in terms of noise. In addition, it also hinted at which criterion could more closely approximate the interpretational behavior of the physician. This study also uncovered some of the possible limitations and caveats of the two types of deterministic logic. The second patient study measured the sensitivities and specificities of the three criteria. It also measured the sensitivities and specificities of the fuzzy rule under different gains. The simulation study allowed comparison of the criteria under different levels of noise modelled by the spread of wave magnitudes. Also with the simulation study, the relationships of a fuzzy gain to the interpretational behavior and stability of the Fuzzy Criterion were explored. Hence a relative comparison of the criteria, in light of the patient studies, could allow limited inferences about the criteria in relation to noise and possible behavior under real conditions.

4.2 Conclusions from Patient Study I

The last two patterns (zero to positive, or positive to zero; Figure 6) seem to suggest that the Fuzzy Criterion is more aggressive than either of the other Criteria (especially the Physician Criteria). Also, the Fuzzy Criterion seems to exhibit a lower interpretational stability (less consistent interpretational behavior). This could be attributed to the arbitrary definition of the interpretational intervals (fuzzy subsets). Altering the gain, the 0-gain "crisp" boundaries (i.e., the absolute boundaries when the gain is zero) , the meaning of positive and negative findings, and/or the confidence assignments would obviously alter the patterns in the Fuzzy Criterion from the ones obtained in this study (15). Since the parameters are dynamically associated together, it may be difficult to predict which parameter or group of parameters to modify, or in what manner the parameters should be modified to make the Fuzzy Criterion more closely approximate the physicians' interpretational behavior and stability. Such alterations could improve the sensitivity or specificity of the Fuzzy Criterion as well as lower the sensitivity and specificity. Since the sensitivity and specificity are not the same statistic, changing one may not affect the other in a like manner. For example, as the second patient study has shown, increasing the gain may increase the sensitivity, but the specificity may be lowered. From this first patient study (see Figure 6, Compiled Fuzzy Criterion), the marginal totals of the Fuzzy Criterion more closely approximate those of the Physician Criteria than do the marginal totals of the Absolute Criterion. Yet, if confidence values of 0% and 25% were chosen to imply that there was no finding for inferior infarction, then the number of positive to positive patterns would be less, with a consequent increase in the tallies for the other patterns. The sensitivity and specificity of the Fuzzy Criterion would also be altered, but it is difficult to predict whether there would be an overall improvement in all four patterns, in terms of sensitivity and specificity. Conceivably, the sensitivity would decrease, and the specificity would increase. In some sense, the Fuzzy Criterion would become more conservative in its interpretative behavior, thus more closely approximating that of the Absolute Criterion. Patient Study II was undertaken to provide useful information on this issue.

4.3 Conclusions from the Simulation Study

The results from this study suggest several interesting possibilities. Altering the size of the interpretation intervals may facilitate the adaptation of the rule to meet a variety of noise levels or clinical conditions. This can be accomplished by adjusting the gain to either dilate or contract the size of the interpretation intervals, i.e., increasing or decreasing the gain, respectively. For instance, the results indicate that it is possible for the Fuzzy Criterion to mimic the interpretational behavior and stability of the Absolute Criterion or closely approximate that of the Relaxed Criterion. A fuzzy rule such as the Fuzzy Criterion could be quickly adjusted to adapt to a range of clinical conditions: e.g., emergency room, assist a physician in making an interpretation, and/or assistance in patient care and other conditions. This could be done by adjusting a parameter such as the gain, which controls the size of the fuzzy subsets or interpretational intervals. The overall interpretational behavior of the fuzzy rule could be adjusted by the practitioner, or one could envision an automated version that could optimize the interpretational behavior based upon the automated record keeping of past performances. This will require further study, both for applicabilty and feasiblity.

The fuzzified rule of the Absolute Criterion, the Fuzzy Criterion, also exhibits a more stable (consistent) interpretative behavior about the interpretation boundaries with respect to noise (18). However, as the gain is reduced through the intermediate values between 1 and 0, inclusively, this stability decreases to that of the Absolute Criterion. Since the behavior profiles of the Fuzzy (when gain = 1) and Relaxed Criterion (the more complex classical rule that is derived from the Absolute Criterion) are so similar (meaning they have similar sensitivities and specificities) , the addition or reduction of noise affects both criteria equally (18).

4.4 Conclusions from Patient Study II

The results from the second patient study suggest that the "fuzzification" of the Absolute Criterion into the Fuzzy Criterion (for a gain equal to one) improves its performance in terms of sensitivity, with a minimum loss in its specificity. In fact, it brings the interpretative behavior more in line with its more complex counterpart, the Relaxed Criterion (which was suggested by the simulation study). In addition, the rule's performance or response also more closely approximates that of the Physician in terms of positive predictive value, sensitivity, and specificity, although it does not reach values obtained by the Relaxed Criterion. Also as suggested in the simulation, the Fuzzy Criterion can exhibit a range of specificities and sensitivities by altering the gain of the criterion. To increase the sensitivity, the gain can be increased. To increase the specificity, the gain can be lowered. Unfortunately, an increase in specificity lowers the sensitivity and vice versa. They cannot be altered independently of each other, except with gains in the region of 0 to 0.75. In this region, an increase in gain has little effect on the specificity. The specificity of the Fuzzy Criterion remains higher than that of the Relaxed Criterion and at the same time the sensitivity of the Fuzzy Criterion is almost twice that of the Absolute Criterion. So within this region it is possible to choose a higher sensitivity with an increase in gain without compromising the specificity of the rule to a great degree. To do this with a classical rule, one would have to change the boundaries, connectives and how they are associated, and/or add additional clauses.

4.5 Project Conclusions

The results seem to indicate that a fuzzy transformation of a classical rule, such as applied in this example, can produce interpretational benefits over that of the untransformed classical rule. In the first patient study, the marginal totals from Figure 6 suggest that the interpretational pattern better approximates that of the physician, even though the Fuzzy Criterion was not as consistent as the Absolute Criterion. The Absolute Criterion outperformed the physician with respect to overall consistency. This suggests that the Absolute Criterion makes classification errors when reviewing data that noisy. In the second patient study, the Fuzzy Criterion exhibited a greater sensitivity than the Absolute Criterion. Also, it was shown that if the gain was only allowed to increase modestly from 0 (at which point the Fuzzy Criterion modelled exactly the Absolute Criterion) to 0.75, there was a substantial increase in the sensitivity (almost twice; 0.30 to 0.56) with only a small decrease in the specificity (0.96 to 0.93). Also, if it is accepted that the Relaxed Criterion more closely approximates the Physician (say in terms of sensitivity or specificity), then comparative results between the Fuzzy and Relaxed Criterion in the simulation also tend to support these findings via transitive inference (by analogy, if a = b, b = c, then a = c).

4.5.1 Examining Why the Rule Based Criteria Did not Exactly Match the Physicians' Interpretational Behavior

The rules examined in these studies did not completely approach the interpretational behavior or stability and flexibility of the physician. Although there were some favorable comparisons, none alone approximated the physicians' behavior. Several factors inherent in the rules and perhaps our knowledge and models of the myocardium preclude a perfect match between the rule based criteria and the Physician.

For example the expert physician seems to possess an ability to dynamically alter the interpretational importance of symptoms or signs according to mechanisms not inherent either in classical or fuzzy logic. The physician can reason in the light of the meaning of the particular clinical situation (meaning natural intelligence- based on experience, rules of the trade, soft criteria, and use of various other pieces of clinical information and "clues"). The physician can extrapolate based upon the evidence presented. For instance, in making the interpretation the physician has access to the complete medical record of the patient (physical exam, patient visitation, electrocardiogram/analysis, lab data, previous history, including past electrocardiograms, and other miscellaneous, but perhaps unobservable or quantitative clues). So the physician can make an interpretation that is quite accurate and precise, at least to the degree establishing what the proper care and therapy for the patient should be (different diagnoses may have a very similar therapy or patient care plan).

The rule-based criteria that were included in this study, on the other hand, only reviewed what was included in the patient record. This included the magnitudes of the Q- and R-waves along with the characterization of the T-waves. Some pertinent information could not be reviewed by these rules. The criteria were not designed to take advantage of electrocardiographic patterns or previous interpretations to evaluate the data more accurately. The rules only evaluated one set of magnitudes per time period. They were not able to review previous interpretations, or the patient as a whole.

Another related reason why the rules did not approach the behavior of the physician was that different physicians may interpret the same data somewhat differently (physician noise). No gold standard was applied to the physician results. One physician may say lateral infarction, instead of perhaps inferior infarction. Hence, even with the physicians there is the element of noise in their interpretations or some degree of uncertainty whether or not the physician was correct in the interpretation. Parenthetically this author wonders if there is always a completely true interpretation or if it is necessary to have a completely true interpretation. After all, the language has a degree of uncertainty. Ultimately, whether the diagnosis is absolutely correct may not be what is most important. For instance, if a diagnosis closely approximates the actual clinical condition, then more than likely, an effective therapy can be prescribed either to treat the disease effectively or at least make the patient more comfortable. Being as close as possible with the interpretation to the true diagnosis, given the current knowledge of medicine and the uncertainty in the patient information, may be all that is required. The physical sciences face a similar issue. The physical sciences deal with significant figures, not necessarily absolute ones, in order to make predictions.

Another reason why the criteria did not match the physician is the physician's ability to deal with different information sources. Specifically, is the electrocardiogram a perfect information source? Even with no noise in the electrocardiogram, does the electrocardiogram provide a complete record of the electro-physio-chemical actions of the myocardium, i.e., an inferior infarction? Is the pathogenesis of myocardial infarctions and the associated symptomology a complete or incomplete model? If the model is not complete, and/or the electrocardiogram does not provide complete information, then the physician seems able to deal with incomplete theories and information sources to make a correct interpretation. It would seem that there is a component of craftmanship in how the physician arrives at an interpretation that cannot be modelled in an expert system at this time. Through experiment and study we should be able to explain and incorporate the craft to enrich the theory and formulate the findings into a more accurate model.

4.5.2 Ways to Improve Performance

Speculatively, it may be possible to increase the performance of the fuzzy rule by modelling the Relaxed Criterion. This could be done by dropping the R-wave magnitude clause or "Conf _3," changing the fuzzy subsets by removing the linear steps, changing what was meant by a yes or no interpretation, adding additional clauses, pattern matching, interpretation based on present and past records, utilizing fuzzy pattern matching, or other fuzzy techniques. However it is questionable if much benefit could be derived in relation to the cost and intensity of the research needed to explore the above proposals adequately. This author feels that in order to take full advantage of Fuzzy Logic, the whole clinical evaluation process should be explored, meaning creating a Fuzzy data base, using Fuzzy rules and Fuzzy reasoning methods. This also means the use of fuzzy membership functions to represent the meaning of clinical terms. However, the modelling of linguistic concepts and reasoning methods could prove to be as labor intensive and controversial in implementation as deriving a statistical framework for assigining Bayesian probabilities for the interpretation of disease conditions.

An increase in the performance of the classical rule was obtained by transforming it into a Fuzzy rule, with some inherent flexibility in its use, by altering the fuzzy subsets or gain. However, the Fuzzy rule could not achieve a higher specificity than the Relaxed Criterion without lowering the sensitivity below the Relaxed Criterion. Also, a higher sensitivity than the Relaxed Criterion could not be achieved without lowering the specificity below that of the Relaxed Criterion. Overall, the more complex classical descendant rule of the Absolute Criterion, the Relaxed Criterion, out performed the fuzzy rule in terms of sensitivity or specificity.

4.5.3 Thoughts on Fuzzy Logic and Imitating Physician Diagnostic Behavior

Owing to the nature of Fuzzy Logic, one can perhaps think of it as a meta-rule set (since it is a logic and set theory) which begins to model the "dynamic decision behavior" of the physician more aptly than a Classical Logic, in that it can change which piece of information is "more clinically important" and provide a graded interpretation. This begins with the process of defining the interpretation intervals or fuzzy subsets. As in this project, each clause of the Classical rule were made into a fuzzy subset which allowed the rule to ascribe membership of a particular data item to the semantic meaning of the clause. In other words the crisp boundaries of the Classical rule were made "soft." A crisp boundary was transformed into an interval. Hence, relatively small changes in the data do not cause large changes in the final outcome of the interpretation by the Fuzzy Criterion. The process was continued with the application of the MAX/MIN rule of composition. For instance, the clauses of fuzzy rules connected by a conjunctive do not give a zero result unless each clause has a confidence or certainty of 0. Finally the process ended with the evaluation through MIN/MAX composition which ascribed membership of all the information or data in the fuzzy subset, inferior infarction. The Fuzzy Criterion gave different confidence values of an interpretation of inferior infarction. These values were 0%, 25%, 50%, 75%, and 100% confidences which are degrees of membership in the set of people suffering from inferior infarction. These values corresponded with: inferior infarction not possible, consider an infarction, inferior infarction possible, inferior infarction probable, and definite inferior infarction. Hence the Fuzzy Criterion is able to give a graded interpretation which can be used to describe a patient's degree of membership in the fuzzy set, people with inferior infarctions, and provide a basis through which small changes in the data have negligible effects in the final interpretation.

These features are not an inherent feature of Classical Logic or rules. For Classical Logic systems, other rules would have to be written in order to describe the membership or degree of certainty of an inferior infarction and the MAX/MIN rule of composition. In addition, small changes in the data could bring about significant outcomes in the final intepretation. For example a 10 microvolt change near a crisp boundary in the Q-wave or R-wave could bring about a complete reversal of the interpretation, leading to a classification error. This was illustrated in Table 2, examples (i, j) and (c ,d). Also, since more rules would be needed to assign membership in a particular set, combinatorial problems of rules would have to be contended with in such a Classical Logic expert system.

4.5.4 Relevance of Project to Diagnostic Systems

One may ask which approach is better, the Classical rules or the Fuzzy rules. At this juncture there can be no definitive answer, for each approach as utilized in these studies has exhibited interpretational weaknesses and strengths.

Yet if one agrees with Zadeh (3) that Fuzzy Logic subsumes predicate logic and probability theory, then it would seem appropriate that an expert system have the capability of implementing a Fuzzy formalism. If conditions warrant Classical approaches, then the database, knowledgebase and inferential mechanisms can be implemented as Classical formalisms. However, if membership or confidence is an issue, or a multivalued logic is implicated, then Fuzzy formalisms may be more appropriate for implementing an expert module or subset to the total system for a particular medical domain.

This author feels that the problem may not be in what approach is used, but that a system is unable to adopt alternative knowledge formalisms, either to implement the reasoning and knowledge representation scheme best suited to solve a given medical problem, or allow a knowledge engineer or practitioner personal discretion in the design of an expert decision module. A diversification of knowledge formalisms in an expert system would allow practitioners to take advantage of the plethora of medical decision schemes available to implement expert modules for a particular medical domain (20).

In conclusion, the different formalisms are our "cognitive tools," which we can use to manipulate models of "real things." These formalisms can also be used as learning tools and a means of changing our mental "viewpoints" and increasing our knowledge of medicine. These cognitive "exercises" are important so that our models more closely approximate "real things" so that our predictions/inferences are more accurate and informative, thus improving the health care of the patient (21, 22).

APPENDIX A

THE CRITERIA

I. Absolute Criterion:
  If { [$q < -50$ and $r/q > -4$ and $R \geq 400$] or [$q < -250$] }
  then inferior infarction

II. Relaxed Criterion:
  If { [$q < -50$ and $r/q > -4$ (and $r \geq 400$)†]
    or [$q < -150$] or [$q < -75$ and $t \neq 2$*] }
  then non-diagnostic q-waves

III. Fuzzy Criterion
  Confidence of Inferior Infarction is determined by:

	MAXIMUM			
	MINIMUM			
Confidence:	Conf_1	Conf_2	Conf_3	Conf_4
0%	$q \geq 0$	$r/q \leq -4$	$r < 250$	$q \geq -100$
25%	$-25 \leq q < 0$	$-4 \leq r/q < -3.5$	$250 \leq r < 300$	$-150 < q \leq -100$
50%	$-50 \leq q < -25$	$-3.5 \leq r/q < -3$	$300 \leq r < 350$	$-200 < q \leq -150$
75%	$-75 \leq q < -50$	$-3 \leq r/q < -2.5$	$350 \leq r < 400$	$-250 < q \leq -200$
100%	$q < -75$	$-2.5 \leq r/q$	$r \geq 400$	$q \leq -250$

These are the three deterministic criteria used in this project. The first two criteria are the HELP system Classical deterministic rules which determine whether or not a person has suffered either an inferior infarction or has an electrocardiographic condition that is characterized by nondiagnostic q-waves (considered to represent inferior infarction if present in the Y-lead). Under such classical rules a patient either has or does not have these conditions. However, Fuzzy formalisms allow values between yes and no, i.e., values between 0% and 100%. The Fuzzy Criterion as implemented in this project could have logical results for inferior infarction of 0%, 25%, 50%, 75%, or 100%. These numbers represent the possibility of inferior infarction. Any confidence greater than or equal to 25% represented inferior infarction in this project.

* A t-wave character not equal to 2 in the patient record was considered an abnormal t-wave; viz., meaning negative or nonexistent.
† This clause used in the simulation study and not used in Patient Study II.

APPENDIX B

HOW TO EVALUATE A FUZZY RULE ACCORDING TO THE MAX/MIN RULE OF FUZZY COMPOSITION

The clauses of deterministic Fuzzy rules are connected through the use of the following connectives: "AND" and "OR". Although these connectives are the same as those used in deterministic Classical rules, their logical operations are different.

Assume that A, B, C, and D can be either Classical or Fuzzy Logical clauses connected by "AND" or "OR". An "AND" connective in a Fuzzy rule implies the Fuzzy intersection of two or more Fuzzy subsets. Hence the minimum membership or confidence of the clauses is taken. On the other hand, Fuzzy clauses connected by an "OR" implies the Fuzzy union of two or more Fuzzy subsets. Hence the maximum membership or confidence of the clauses is taken.

The following examples that contrast the evaluations of Classical and Fuzzy clauses should help the reader understand some of the rudimentary logical operations and rule evaluations of Fuzzy Logic.

- Deterministic Classical rule evaluations:

e.g., Truth Table for the Clauses A and B.

A	**B**	**A and B**	**A or B**
T(1)	T(1)	T(1)	T(1)
T(1)	F(0)	F(0)	T(1)
F(0)	T(1)	F(0)	T(1)
F(0)	F(0)	F(0)	F(0)

A deterministic Classical rule has clauses that are either true or false, and based upon the truth of the clauses and the logical connectives, a rule is either true or false.

• Deterministic Fuzzy rule evaluations:

The membership, confidence, or certainty of a clause can be shown in the following manner: m/Clause. The "m" is an element of [0,1] and represents the confidence of a clause.

A confidence table, which is analogous to Truth table for Classical rules, is shown below to emphasize the Fuzzy evaluation process.

m/A	m/B	A and B	A or B
1/A	1/B	1	1
1/A	0/B	0	1
0/A	1/B	0	1
0/A	0/B	0	0

If the membership or confidence values mimic the truth values of the Classical rules, the final evaluations of the rules are essentially the same. But if intermediate or values between 0 and 1 are used to represent the confidences of the clauses, the final evaluations are different.

A confidence table for intermediate confidence values for the Fuzzy evaluation process can look like the following.

m/A	m/B	A and B	A or B
0.90/A	0.93/B	0.90	0.93
0.80/A	1.00/B	0.80	1.00
1.00/A	0.80/B	0.80	1.00
0.50/A	0.25/B	0.25	0.50
0.10/A	0.01/B	0.01	0.10
0.53/A	0.53/B	0.53	0.53

The evaluations no longer represent definite outcomes but instead represent intermediate possibilities between and including 0 and 1. Confidence values represent subjective degrees of uncertainty or noise in clauses, propositions, or other logical statements.

APPENDIX C

FURTHER EXPLORATIONS WITH THE EVALUATIONOF FUZZY RULES

Given the following clauses with the certainty or confidence values and logical connectives:

Example 1:

{ 0.50/A and 0.25/B } and { 0.25/C or 1.00/D } =
min { min [0.50, 0.25], max [0.25, 1.00] } =
min { 0.25, 1.00 } =
0.25 the confidence or certainty in the four clauses.

Example 2:

{ 0.50/A and 0.25/B } or { 0.25/C or 1.00/D } =
max { min [0.50, 0.25], max [0.25, 1.00] } =
max { 0.25, 1.00 } =
1.00 = the confidence in the four clauses

Example 3:

{ 0.50/A and 0.25/B } or { 0.25/C and 1.00/D } =
max { min [0.50, 0.25], min [0.25, 1.00] } =
max { 0.25, 0.25 } =
0.25 = the confidence in the four clauses

Example 4:

{ 0.50/A and 0.25/B } and { 0.25/C and 1.00/D } =
min { min [0.50, 0.25], min [0.25, 1.00] } =
min { 0.25, 0.25 } =
0.25 = the confidence in the four clauses

Example 5:

{ 0.50/A and 0.25/B } and { 0.75/C and 1.00/D } =
min { min [0.50, 0.25], min [0.75, 1.00] =
min { 0.25, 0.75 }
0.25 = the confidence in the four clauses

Example 6:

{ 0.50/A and 0.25/B } or { 0.75/C and 1.00/D } =
max { min [0.50, 0.25], min [0.75, 1.00] =
max { 0.25, 0.75 }
0.75 = the confidence in the four clauses

As can be seen from these examples, depending on the confidence values of the individual clauses, the logical connectives and the logical flow, the evaluations of the clauses can be quite different.

APPENDIX D

ILLUSTRATION OF THE MEANING OF GAIN IN THE FUZZY CRITERION

```
if
  (q-wave < -75.0)
then confidence_1 = 1.00

else if
  {q-wave < [-75 + (gain x 25)] and (q-wave ≥ -75)}
then confidence_1 = 0.75

else if
  {q-wave < [-75 + (gain x 50)] and [q-wave ≥ -75 + (gain x 25)]}
then confidence_1 = 0.50

else if
  {q-wave < [-75 + (gain x 75)] and [q-wave ≥ -75 + (gain x 50)]}
then confidence_1 = 0.25

else if
  q-wave ≥ -75 + (gain x 75)
then confidence_1 = 0.00
```

Gain, as used in the context of this project, is a factor that multiplies the step width of the different domains in each clause. In the case of Confidence_1, each domain is separated by 25 microvolts if the gain is equal to one. On the other hand, if the gain is equal to 1.2, each domain is separated by 31.5 microvolts. Furthermore, if the gain is equal to 0.5, then each domain is separated by 12.5 microvolts. In other words, the gain either increases (dilates) or decreases (contracts) the separate domains of each confidence.

In a like manner, the gain is applied to the other clauses of the Fuzzy Criterion.

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